The Gender Gap in Elite-Voter Responsiveness Online*

Zachary P. Dickson[§]

[§]London School of Economics, z.dickson@lse.ac.uk

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Abstract

A number of important studies have documented gender gaps in the effectiveness or performance of individual representatives. Yet, whether these differences are observable when it comes to responsiveness to public opinion is unclear. In this article, I examine the degree to which representatives use social media to dynamically respond to shifts in issue salience among the electorate. After combining nearly 400 bi-weekly repeated public opinion surveys from YouGov asking voters about their issue priorities, I trained a large language model to classify the universe of elected US and UK representatives' social media messages on Twitter to the same issues. Findings reveal that women representatives demonstrate greater responsiveness than their male counterparts to shifts in issue salience according to both women and men constituents. Despite an overall bias toward male constituents, women representatives play a crucial role in narrowing the gender gap by consistently aligning their attention with the issues prioritized by women constituents. These findings not only contribute to our understanding of elite-voter responsiveness but also underscore the substantive benefits that women representatives provide for *all* constituents.

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1 Introduction

The extent to which descriptive representation – representation by members who share a common background or physical characteristics with the represented – leads to greater substantive representation – representation whereby members act in the interest of the represented – is the subject of decades of thoughtful scholarly literature on women's representation (Pitkin 1967; Mansbridge 1999; Phillips 1998; Campbell, Childs, and Lovenduski 2010; Celis and Childs 2012; Reingold 2008; Barnes 2016; Anzia and Berry 2011; Reingold 2008; Bratton and Ray 2002; Dovi 2007; Clayton et al. 2019; Wängnerud 2009; Kittilson 2008; Thomas 1991; Lowande, Ritchie, and Lauterbach 2019; Carroll 2003; Chattopadhyay and Duflo 2004; Beckwith 2014; Weeks 2022). Yet, empirical findings on the link between descriptive and substantive representation are mixed, with some studies finding that the share of women in power leads to better outcomes for women constituents (Ferland 2020; Clayton et al. 2019), while others find that the share of women officeholders has little or no effect (Homola 2019; Dingler, Kroeber, and Fortin-Rittberger 2019; Reher 2018).

Several recent studies, however, take a different angle and instead suggest that when representatives are able to act in an individual capacity, they go further than their male peers to advance the substantive interests of *all* constituents. These studies point to greater barriers to entry into politics and sex-based discrimination in the electoral process, both of which effectively create a scenario in which women in power, conditional on winning elected office, tend to be of higher quality than their male peers (Lazarus and Steigerwalt 2018; Anzia and Berry 2011; Thomsen and Sanders 2020). Support for this argument comes from a number of studies focusing on the US context. For instance, congresswomen are shown to be more responsive to constituency service requests (Thomsen and Sanders 2020), to be more collaborative (Barnes 2016; Volden, Wiseman, and Wittmer 2013), to give more speeches on the House Floor (Pearson and Dancey 2011), and to deliver greater funding for their electoral districts (Anzia and Berry 2011).

Although this literature convincingly demonstrates that women representatives 'out-perform' their male colleagues on a number of legislative tasks, the extent to which public opinion drives these gendered differences remains unclear. In this article, I study the relationship between dynamic public salience and the attention of representatives in the primary legislative bodies of the US and UK – the US House of Representatives and the UK House of Commons. Methodologically, I combine nearly 400 repeated bi-weekly public opinion surveys from YouGov asking voters about their issue priorities in the United States and United Kingdom. I use these high-quality, representative surveys to capture the dynamic salience of different issues according to different segments of the electorate, effectively creating dynamic issue agendas for women and men constituents in each country. I then create similar issue agendas for representatives by focusing on the content of their messages sent on the social media platform Twitter (now X). After combining over three million messages sent between 2018 and 2022, I trained and validated a large language model for classification of each of the messages according to the issues domains for which public opinion data were available.

Results from vector autoregressions and fixed effects specifications suggest that in both countries, women constituents receive less attention from representatives than men constituents. However, women representatives narrow this gender gap by consistently demonstrating greater responsiveness than men representatives to shifts in salience from women constituents. Importantly, I find that greater responsiveness from women representatives does not come at the expense of responsiveness to men constituents. In fact, the results illustrate that women constituents similarly outperform their male counterparts in responsiveness to men constituents as well. These findings are consistent across both countries and are robust to a number of modelling specifications, including several alternative explanations and robustness checks.

The findings of the article therefore contribute to the literature on elite-voter responsiveness and gendered patterns in representatives' behavior in several important ways. First, a focus on the substance of representatives' communication on social media offers a new perspective on the substantive representation of voters (Pitkin 1967). Although representatives' communication on social media may not necessarily translate to legislative action, research shows that voters want their representatives to address policy issues on social media (Giger et al. 2021), and may even associate satisfaction with democracy with the degree to which representatives verbally emphasize the issues that are important to them (Reher 2016).

The findings moreover constitute an important contribution to the literature on gendered patterns in representatives' behavior by providing insight into the individual responsiveness of representatives to constituents. Given that political institutions and party discipline constrain the degree to which representatives can act in an individual capacity (Kam 2009; Clayton and Zetterberg 2021), representatives may indeed wish to signal to the electorate that they are aware of and responsive to the issues that are most important to them, but may be unable to do so in traditional legislative settings. Social media provides representatives with an opportunity to act in an individual capacity, and to distinguish themselves from the programmatic party agenda while speaking directly to constituents (Russell 2021b).

Finally, the study is important for understanding the ways in which representatives respond to constituents in real time. Although a number of studies have examined congruence between parties or representatives and the preferences of the electorate, politics is a dynamic process and public attitudes are constantly in flux. By focusing on high-frequency repeated surveys and millions of messages sent by representatives on social media, the study is able to capture responsiveness as a dynamic process, differentiating between mandate fulfillment and the degree to which representatives actively adapt to changes in the electorate's opinions.

The remainder of the article proceeds as follows. In the next section, I outline the mechanisms underlying the 'out-performance' argument before highlighting expectations for dynamic responsiveness. The following section provides the research design and details the data collection and analysis process. Section 4 provided the results, which are followed by robustness checks and a discussion.

2 Gender & The 'Out-Performance' Argument

A number of studies that highlight gender differences in legislative behavior show that women outperform their male peers in a number of political and legislative domains (Lazarus and Steigerwalt 2018; Barnes 2016; Holman 2014; Thomsen and Sanders 2020). Among the first to demonstrate this, Anzia and Berry (2011) showed that US congresswomen were more effective than congressmen at securing funds for their respective districts. The authors reconcile two strands of research on sex-based discrimination, arguing that at least two forms of "sex-based selection" result in higher quality women candidates in relation to men. First, compared to male candidates, women tend to be more concerned about their political viability and credentials. For example, Lawless and Fox (2005) demonstrated that women consistently underestimate their qualifications for office, even when such qualifications are matched with male candidates who believe that they are qualified. Moreover, women candidates may have a higher aversion to political competition (Preece and Stoddard 2015), or be more likely to believe that they have more to lose from an unsuccessful bid at elected office than men (Lawless and Fox 2005). These beliefs prove to be valid as well. Female candidates often face greater electoral competition (Lawless and Pearson 2008), face greater challenges raising campaign funds (Jenkins 2007), and receive less support from party organizations (Sanbonmatsu 2010). Therefore, the decision to run for elected office is gendered, with women likely to associate higher costs with running for political office than men.

The second explanation for the out-performance of women candidates focuses on the role of sex-based selection in elections. A number of studies highlight the role of gendered stereotypes and gender bias in the electoral process (Bauer 2015; Sanbonmatsu 2002; Boussalis et al. 2021; Lovenduski 2005; Ashworth, Berry, and Bueno de Mesquita 2024; Cassese and Holman 2018). This bias is often attributed to the fact that voters tend to privilege male over female characteristics (Bauer 2015; Sanbonmatsu 2002; Boussalis et al. 2021). Consequently, to the extent that women candidates are more likely to embody characteristics typically associated with women – or be subjected to stereotypes that marginalize traditionally feminine characteristics[1] – voters may disproportionately discount women candidates at the ballot box.

A third explanation for the out-performance of women in elected office that has been advanced in the context of legislative performance specifically points to institutional constraints that privilege masculinity. Even once elected, women face disproportionate barriers in the legislature that requires them to work harder to achieve the same level of success as their male colleagues. Masculinity is both embedded and hegemonic in political institutions, which often deem traditionally feminine behaviors to being emotional, irrational and weak (Lister 1997; Lovenduski 2005). Therefore, for women to be successful in legislatures, they must compensate for a lack of power and opportunity (Barnes 2016; Lazarus and Steigerwalt 2018; Bauer 2020).

2.1 What about Responsiveness to Public Opinion?

Each of these three aforementioned explanations act in combination to create a scenario in which "only the most talented, hardest working female candidates will succeed in the electoral

1. Although see Hargrave and Blumenau (2022) and Hargrave (2023) for a different perspective in the British context.

process" (Anzia and Berry 2011, p. 478). Yet, while many important studies find support for the out-performance argument by demonstrating that women representatives are proactive in their legislative behavior (Höhmann 2020; Kweon and Ryan 2022), the wider literature on representation has also highlighted the importance of the reactive behaviors of representatives, and the extent to which representatives are responsive to the preferences of their constituents (Stimson, MacKuen, and Erikson 1995; Erikson, MacKuen, Stimson, et al. 2002; Burstein 2003; Soroka and Wlezien 2010; Pitkin 1967; Powell Jr. 2000). Although responsiveness is only one element of substantive representation, it is nonetheless an important condition and features prominently in Pitkin's definition of substantive representation. Moreover, voters value responsiveness from their representatives (Carey 2008), and voters' satisfaction with democracy has been shown to be a function of the degree to which representatives respond to their issue concerns (Reher 2016)

Several studies examine responsiveness or policy congruence in the context of representatives' gender. For example, Griffin, Newman, and Wolbrecht (2012) examine dyadic policy representation in the US Congress and find that having a women representative does not improve congruence. In contrast, Höhmann (2020) shows that women representatives in the German Bundestag demonstrate greater responsiveness on women's issues by raising more parliamentary questions. Clayton et al. (2019) find that women representatives prioritize similar issues as women constituents, enhancing congruence, but that the relationship is also a function of the strength of democratic institutions. Differing slightly, Thomsen and Sanders (2020) use an audit study to examine gender differences in responsiveness to constituent requests. The authors find that women representatives are indeed more responsive than men, but that the gender of the constituent who makes the request does not enhance the relationship.

Several studies within the descriptive representation literature also examine the degree to which an increase in the number of women in parliament leads to a more responsive government. Among these studies, several find that an increase in the proportion of women in parliament leads to a more responsive or congruent government (Ferland 2020; Forman-Rabinovici and Sommer 2019), while others find little or no effect (Reher 2018; Homola 2019; Dingler, Kroeber, and Fortin-Rittberger 2019).

Although this literature is somewhat mixed when it comes to the relationship between gender and responsiveness to public opinion, the literature making the 'out-performance' argument suggests that when representatives are able to act in an individual capacity, they go further to advance the substantive interests of constituents. I therefore expect that in contexts in which representatives have the capacity to respond to public opinion individually, women representatives will make a greater effort to do so in relation to men representatives. Specifically, I expect that women representatives will be more active in using the platforms available to them to signal to constituents that they are aware of and responsive to salient public issues. Moreover, I expect responsiveness to be dynamic, and that changes in public salience will be more predictive of later changes in the attention of women representatives compared to men. This expectation is formalized in the following hypothesis:

> **Hypothesis:** *Women representatives are more responsive than their male colleagues to changes in public opinion.*

3 Dynamic Responsiveness

To test the primary hypothesis, I examine correspondence between the salience of different issues according to the public and the amount of attention those issues receive from representatives. Specifically, I focus on the extent to which the level of importance women and men attribute to different issues predicts the level of attention women and men representatives devote to the same issues. This conceptualization of responsiveness is also referred to as dynamic agenda responsiveness or issue responsiveness in the representation literature (Traber et al. 2022; Klüver and Spoon 2016).

To understand dynamic responsiveness to public issue salience, measurement of both issue salience and representatives' attention are required. To capture issue salience, I rely on repeated surveys asking respondents to identify the most important issue facing the country. Although such surveys are not without their limitations (Wlezien 2005; Dennison 2019), they are widely used to measure issue salience in the literature on public opinion and political behavior (Soroka and Wlezien 2010; Klüver and Spoon 2016; Yildirim 2022; Traber et al. 2022; Reher 2018). Moreover, when combined over time, they capture changes in public salience according to women and men constituents, which makes them well-suited to the task of creating dynamic agendas for different segments of the electorate.

To capture the attention of representatives, I relied on data from Twitter (Twitter 2021). There are several advantages of using the social media messages of representatives to understand their attention. First, tweets are concise declarations of interests and focus. Due to the character limits on tweets, representatives (and all users) are required to convey clear statements that leave little room for ambiguity. Second, tweets—and social media more broadly—give representatives the opportunity to signal their preferences outside of the institutional constraints of parliament (Sältzer 2020; Peeters, Van Aelst, and Praet 2021). Moreover, past research has shown that voters prefer their representatives to address policy issues on Twitter (Giger et al. 2021) and that MPs in turn use Twitter to build policy reputations with constituents (Russell 2021a). A third advantage of using communication data from Twitter is that it allows for capturing the dynamic attention of legislators over time to the same issues that are prioritized by voters. Whereas legislative bills or roll call votes occur sporadically and may be planned long before a shift in the electorate's attention, representatives can use social media to signal to the electorate that they are aware of and responding to the issues that are most important to them in real time.

By relying on messages sent directly from the personal accounts of representatives, an assumption that is made is that the messages are sent from the representatives themselves or by authorized staff on behalf of the representative. Although representatives may delegate their social media accounts to staff, I assume that the substantive content of the messages is nonetheless a direct reflection of representatives' wishes. This is a common assumption made in studies that use social media or other forms of communication such as newsletters to understand representation (Sältzer 2020; Peeters, Van Aelst, and Praet 2021; Blum, Cormack, and Shoub 2023).

3.1 Measuring Public Issue Salience

Measuring public issue salience required collecting and combining every nationally-representative YouGov survey fielded in the US and UK that asked voters what they believed to be the most important issue facing the country (YouGov 2021a, 2021b). Between 2018 and 2022, YouGov fielded 204 surveys in the US and 182 surveys in the UK. Sample size in the US surveys included a minimum of 627 and a miximum of 4,082 adults, and the UK surveys included a minimum of

971 and a maximum of 5,226 adults. All surveys are publicly available and were downloaded directly from the YouGov website.[2]

The surveys vary slightly in the frequency with which they were conducted, but most are conducted every 1–2 weeks with subtle exceptions around holidays. One limitation of the surveys, however, is that respondents may select only one issue in the US, while UK respondents can select up to three issues. I address this limitation by analyzing the two countries separately. There are also subtle differences in the set of issues from which respondents may select. For example, the UK surveys allow for the selection of the "The UK leaving the EU," which was one of the most salient issues in the country. However, Brexit (e.g. "The UK leaving the EU") was not as key of an issue in the US, and was not an option in the US surveys. Therefore, "The UK leaving the EU" was only included in the UK analysis. Additionally, only issues that could be harmonized over the entire analysis were included, which amounted to 8 issues in the US and 9 issues in the UK. These issues included 'health', 'crime', 'tax', 'education', 'immigration', 'economy', 'environment', 'defense' and 'Brexit' (UK only).

Following similar studies of dynamic responsiveness (Traber et al. 2022; Klüver and Spoon 2016), measurement of the public's issue salience for different issue priorities is based on the percentage of respondents who select each of the issues to be the most important issue, excluding respondents who replied with "don't know". For example, if 15% of respondents selected immigration as the most important issue, then the level of salience for that issue would be 0.15. The aim of measuring public salience in this way is to capture changes over time rather than the absolute salience of an issue at a given time. This measurement is used for each of the issues in the surveys, and for both of the countries in the analysis according to gender of the respondent.

Figure 1 and Figure 2 present public issue salience resulting from combining the surveys conducted in the US and UK from 2018–2022. In the figures, each point represents a separate survey and the y-axis is the percentage of voters who selected each issue to be the most important issue in the survey according to the gender of the respondent.

The figures demonstrate considerable variation in the salience of different issues over time, with strong correlations between women and men on many of the issues. The influence of

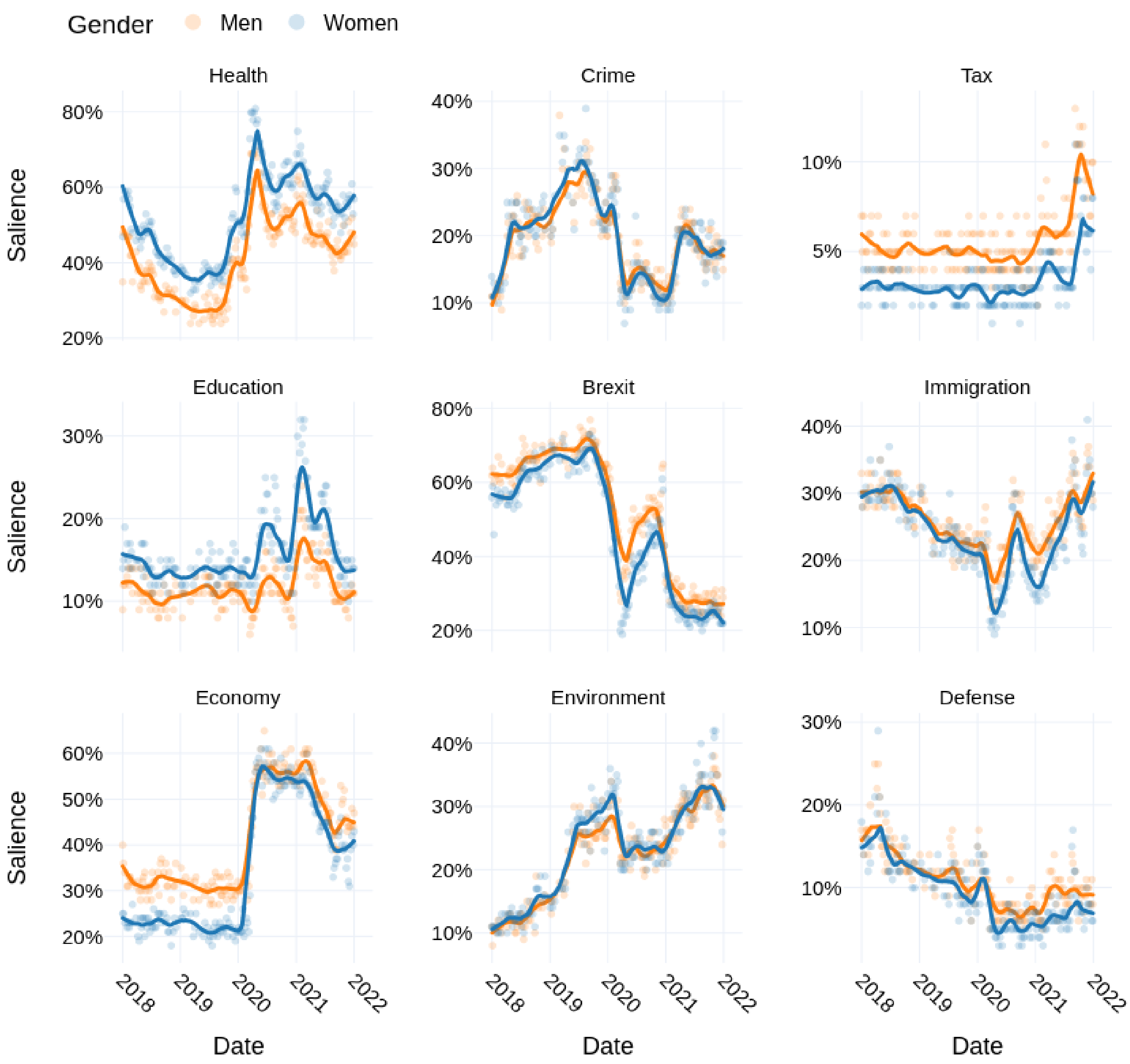
2. Methodology and all available downloads for the YouGov surveys are available for the UK and US, respectively: UK; US.

Figure 1: Dynamic Public Issue Salience in the US – 2018-2022

Note: Floating y-axis. The y-axis is the percentage of the population identifying an issue as one of the most important issues facing the country. Respondents may choose only one issue. Data rely on combined YouGov public opinion surveys conducted in the US from representative populations of men and women. Each point represents a separate survey and the trend line is the 12-survey moving average.

COVID-19 on the salience of health and the economy is clearly visible in both countries, with men tending to prioritize the economy compared to women, and women tending to prioritize health compared to men. Education and taxes also appear to be gendered in both countries, with women prioritizing education and men prioritizing taxes. In the UK, Brexit was one of the most salient issues throughout the time period, but would drop in salience dramatically following the UK's exit from the EU in 2020.

Figure 2: Dynamic Public Issue Salience in the UK – 2018-2022



Note: Floating y-axis. The y-axis is the percentage of the population identifying an issue as one of the most important issues facing the country. Respondents may choose up to three issues. Data rely on combined YouGov public opinion surveys conducted in the UK from representative populations of men and women. Each point represents a separate survey.

3.2 Measuring Representatives' Issue Attention

To measure representatives' attention to the different issues presented in Figure 1 and Figure 2, I collected every publicly available tweet sent by elected legislators in the US House of Representatives and MPs in the UK House of Commons between 2018–2022. Tweets sent from representatives were collected through the Twitter Academic Research Track API (Twitter 2021). Although no longer in use, the API had been made specifically for academic researchers and afforded expanded access to Twitter data for research purposes. After dropping all messages that did not contain text from the user (i.e. retweets without new quotes), there were 3,165,899 messages across both countries. In total, 1,032,650 were sent by women representatives and 2,133,249 were sent by men. This differential roughly reflects the two-to-one makeup of men and women in the two legislative bodies. I present descriptive statistics the the data in Appendix C.

After collecting the Twitter messages, a method for determining the issue of each message was required. For this task, I fine-tuned a pre-trained large language model to predict the issue of each message.[3] As tweets are relatively short and concise, I used a pre-trained BERT model (Bidirectional Encoder Representations from Transformers) as the base model. BERT is a large language model that was pre-trained on a large corpus of English text, including a corpus of English Wikipedia and thousands of textbooks (Devlin et al. 2018). An additional layer can then be fine-tuned in order to perform specific tasks. For the task at hand, the pre-trained model was fine-tuned to classify representatives' messages according to the issue they addressed. To fine tune the model, I used an annotated training data set of 7,000 tweets from the wider set of representatives' messages. After fine-tuning, the model achieved a weighted average F1 score of 0.77 on a held-out test set that had not been seen by the model. Further details about the training and validation procedures are provided in Appendix D.

After classifying each message, I created a measure of representatives' attention by using the proportion of messages sent by each representative about each issue.[4] This measure of attention follows the logic that representatives face real-world trade-offs in allocating their attention to different issues, and are therefore required to strategically attend to certain issues with an opportunity cost associated with ignoring others (Jones and Baumgartner 2005). Moreover, measuring attention as a proportion accounts for the fact that representatives do not participate equally on Twitter. The same measure of attention was used for each of the issues in the analysis, and for both of the countries in the analysis.

3. In addition to the 9 issues presented in Figure 2, I also included a category for messages that did not pertain to any of the available issues. These messages were non-political and might include, for example, "Happy New Years" or "Happy 4th of July".

4. For example, in the individual datasets, $\text{Attention}_{[i,j,t]} = \frac{\text{Number of tweets legislator } i \text{ sends about issue } j \text{ at time } t}{\sum_{j'} \text{Number of tweets legislator } isends \text{ at time } t}$.

3.2.1 What Does "Attention" Look Like?

During the time the data were collected, Twitter messages were limited to 280 characters, which is roughly equivalent to 50 words. As such, Twitter messages are not long enough to address a complex policy issue in detail. Instead, Twitter messages are often used to signal support or opposition to a policy or to highlight a specific aspect of an issue. These expressions constitute a representatives' attention to different issues. For example, the following is a tweet sent from Barry Gardiner, a UK Labour Party MP, in early 2021:

> If you really wanted safe and legal routes for refugees why did you close the Dubs Scheme, stop family reunion from Europe and restrict the Syrian Resettlement scheme? These plans create a limbo without hope for people fleeing violence and war.

The message references the UK government's vote against the Dubs Amendment, which would have allowed unaccompanied child refugees in the UK to reunite with their families. While the message may not be long enough to address the issue in detail, it signals the representative's attention to immigration and was classified as such by the trained model.

Across the Atlantic in the US, representatives were similarly focusing on immigration policy on Twitter in early 2021. The following is a tweet sent from Republican Representative Steve Scalise in March 2021. With the message, Scalise shared a video of a Democratic official from Texas speaking about the situation at the US-Mexico border.

> Attention Joe Biden:
>
> A Texas DEMOCRAT who represents border towns is calling out your policies:
>
> "The way that we're doing it right now is catastrophic and is a recipe for disaster"
>
> "It won't be long before we have tens of thousands of people showing up to our border"

In the message, Scalise highlights the potential threat anticipated by a local official created by President Biden's immigration policies. This message addresses the issue of immigration and was classified by the model accordingly.

The two messages above are examples of how representatives use Twitter to signal their attention to a particular issue. However, both messages expressed opposition to existing policy. At the same time, representatives also use Twitter to signal support. For example, the following is a tweet sent from Democrat Representative Mary Scanlon in late 2021:

> We can't count on SCOTUS to protect our reproductive freedom. The Senate must pass the Women's Health Protection Act now.

The congresswomen displays her support for a women's health bill in calling for the Senate to support the bill. The message was classified as addressing the issue of health.

Representatives also show their attention to issues by highlighting constituency service or by advertising their own work on an issue. For example, the following is a tweet sent from Labour MP Marie Rimmer in mid-2019.

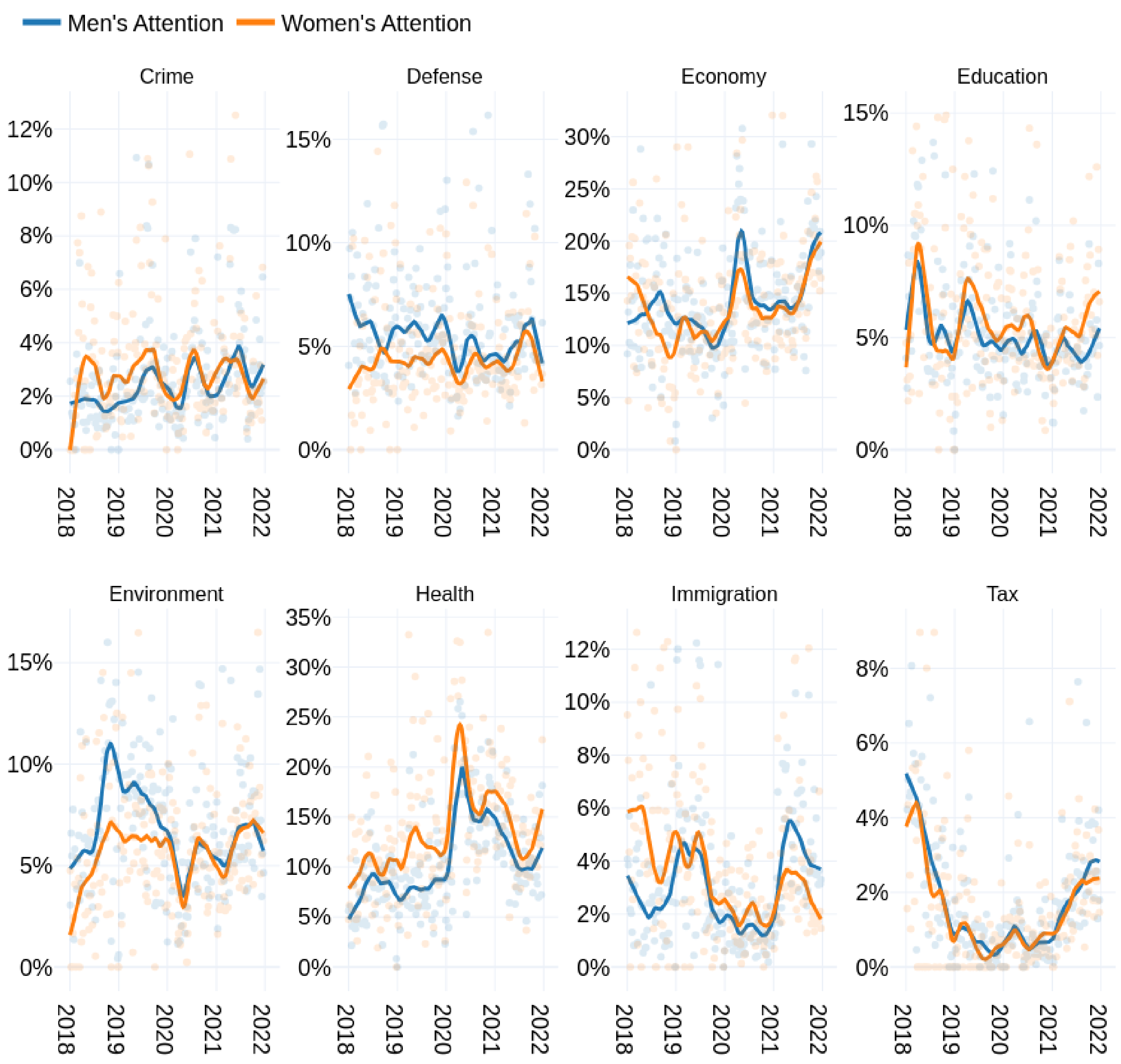
> I was glad to be able to meet with some of my constituents today to discuss the threat of the #ClimateEmergency and what actions I could take as an MP to help fight it. I constantly receive correspondence on this issue from constituents and I'm glad to support them #TheTimeIsNow

With the message, Rimmer shared an image of herself with several constituents at what appears to be a local climate protest. The message was classified by the model as addressing the issue of the environment.

Although each of the example messages above are different in their content, they all signal a representative's attention to a particular issue. Individually, there are limits to what can be learned from a single message. However, representatives send thousands of messages that similarly signal their attention to different issues. When combined over time, these messages can provide a temporal picture of a representative's attention to the issues that matter to constituents.

Figure 3 and Figure 4 present the levels of attention that male and female representatives give to each of the eight different issues. As mentioned previously, attention is the proportion of messages about a given issue at a given time period. In both countries, the time periods are determined by the times at which the public opinion surveys were fielded.

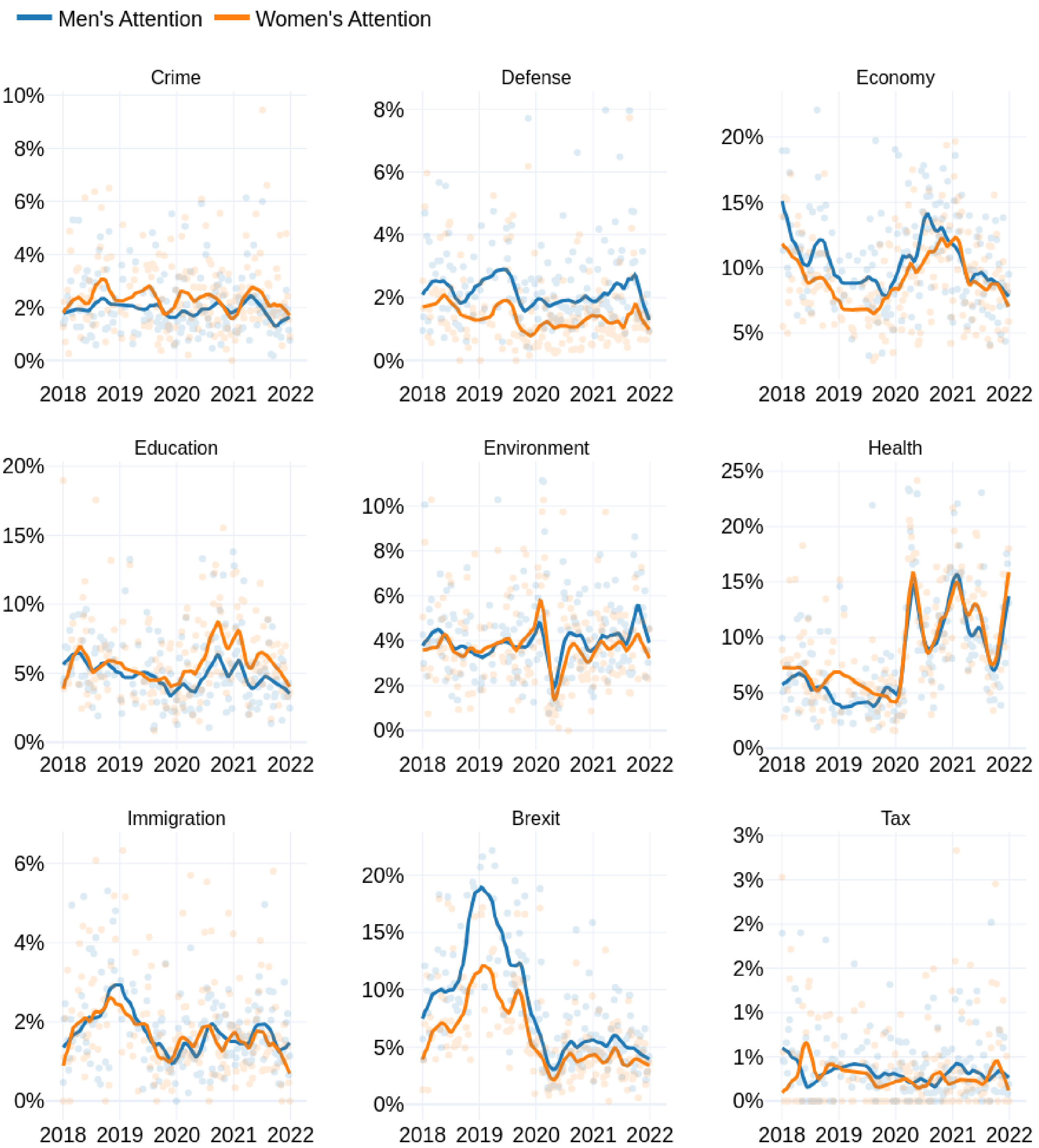
Figure 3: Dynamic issue attention of United States representatives by gender



Note: The y-axis is percentage of representatives' Twitter messages that address a specific issue as a proportion of their messages about all issues. Data are presented using using 4-month time periods for attention. Descriptive statistics are available in Appendix C.

There are several key trends that can be observed in the attention data. First, while there is significant variation in attention over time and between issues, attention is strongly correlated between women and men representatives in both countries. Differing from the issue salience figures above, there are not the same clear gender differences in which women or men consistently prioritize an issue over the other. In the US and UK, women representatives appear to give more attention to crime and education, while men representatives appear to give more

Figure 4: Dynamic issue attention of United Kingdom representatives by gender



Note: The y-axis is percentage of representatives' Twitter messages that address a specific issue as a proportion of their messages about all issues. Data are presented using using 4-month rolling average. Descriptive statistics are available in Appendix C.

attention to defense and to some degree the economy. Notably, attention to health and the economy attracts the most attention in both countries, which appears to be the case even before the COVID-19 pandemic and is fairly consistent with the issue salience figures above (see Figure 2 and Figure 1).

3.3 Estimation

To estimate the effects of public salience on representatives' attention, I rely on two strategies.[5] In the first estimation strategy, estimate the effects of public salience on representatives' attention using vector autoregressions (VARs). This strategy included aggregated the data by representatives' gender and creating four time-series for each country – two for representatives attention (by gender) and two for public salience (by gender). In the second estimation strategy, I estimate the effects of public salience on representatives' attention using fixed effects regressions. This strategy included using individual level data which includes measures for each representative separately and therefore allows for the inclusion of various control variables at the individual legislator level. While each estimation strategy has its own strengths and weaknesses, the two strategies are complementary and are intended to provide a more robust understanding of the relationship between public issue priorities and representatives' attention.

The vector autoregression models are particularly well suited for an analysis of the time series data because each variable in the series is modelled as a function of its lagged outcomes and the lagged outcomes of the other variables in the series. This strategy not only accounts for the temporal structure of the data, it also allows for estimation of the influence of all the variables in the series on each other. For example, while the expectation is that representatives respond to public salience (i.e. public salience predicts representatives' issue attention), it is also possible that representatives lead the public in their attention to issues. The VAR approach allows for disentangling these relationships. Similar strategies have also been employed in the analysis of dynamic social media data (Widmann 2022) and specifically in analyses of responsiveness from politicians (Gilardi et al. 2022; Barberá et al. 2019). A shortcoming of the VAR models, however, is that each series in the model is pooled, which means that the results average over

5. These two strategies required different datasets. In the first datasets (one for each country), I created time series for women and men representatives attention and women and men's salience. The result was a 1632×4 matrix for the US and a 1638×4 matrix for the UK, indexed by issue and date. (Each dataset contains four series – one of men representatives' attention, one for women representatives' attention, one for men's salience and one for women's salience. In the US data, there were 204 surveys with 8 issues (1632) and the UK data had 182 surveys with 9 issues (1638).) In the second datasets for the individual level analysis, I indexed the data according to representative, issue, and date of the survey, with a separate column for representatives' gender. In both datasets, the public salience data were matched on issue and survey date. Descriptive statistics are provided in Appendix C.

differences across the various issue domains included in the analysis. I address this concern with the fixed effects models in the second estimation strategy described further below.

The VAR models can be formalized using the following equation:

$$Z_{g,i,t} = \alpha + \sum_{i} \sum_{P \leq 10} \beta_{p.i} Y_{g,t-p} + M_{g,t-p} + N_{t-p} + \varepsilon_{g,i,t} \tag{1}$$

Where $Z_{g,i,t}$ is the attention of representatives with gender g to issue i at time t, $Y_{g,i,t-p}$ is the salience of issue i for gender g at time $t-p$, $M_{g,i,t-p}$ is representatives' lagged attention at time $t-p$, and N_{t-p} is lagged issue salience at time $t-p$.

For each specification, the lag structure was selected using the optimal AIC (Akaike information criterion) for the series with an upper bound of 10 lags (approximately 10 weeks) (Wei 2019; Akaike 1969). In both countries, the optimal lag structure was identified as 9 periods using the AIC. I present all results from the time series specifications as cumulative impulse response functions (IRFs). This method presents the cumulative effects of one series on another series given a 1 standard deviation increase. This provides an understanding of the ways in which the effects of one variable act on another over time. All estimates were made using the `statsmodels` library in Python (Seabold and Perktold 2010). For all proportion data (e.g. attention and salience), I use the log ratio, which is common practice when using compositional data (Greenacre 2021).

4 Results

4.1 Responsiveness to Public Issue Priorities

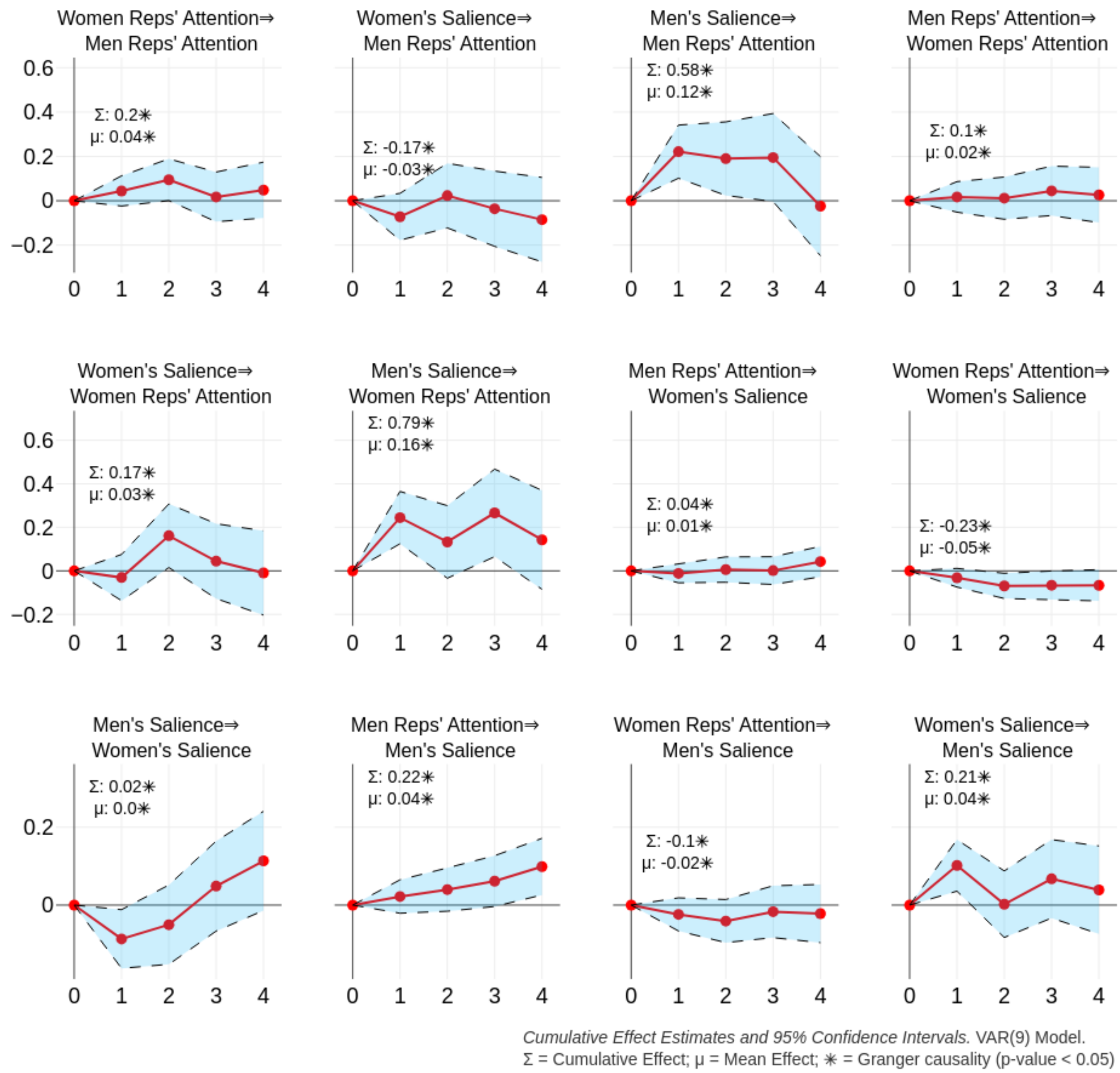
I present the results of the VAR models in two ways. First, I present the results in table format in Appendix F. Second, I visualize the results as cumulative impulse response functions (IRFs) that capture the dynamic effects of public salience on representatives' attention in Figure 5 and Figure 6. At first glance, the figures can appear overwhelming given that each of the variables in the series – women and men's issue salience and women and men representatives' attention – can influence *and be influenced by* the other variables in the series. However, both figures follow the same pattern. In each of the two figures, each subplot is labeled according to the influencing variable and the variable that is influenced. For example, the first subplot in the first row of Figure 5 that is labeled “Women Reps’ Attention → Male Reps’ Attention” presents the estimates for the cumulative effects of women representatives’ attention on men representatives’ attention. The cumulative effects are portrayed dynamically over four survey periods in each subplot, which amounts to approximately four weeks. A red line captures that estimate, and the shaded area indicates 95% confidence intervals. Additionally, in each subplot, the cumulative effect and the average effects over the four survey periods is presented in the top right-hand corner of each respective subplot. In the case that the estimates meet the threshold for Granger causality (Granger and Newbold 2014), which means that lagged changes in the influencing variable consistently predict subsequent changes in the outcome variable (Granger and Newbold 2014), the estimates are accompanied by a star.

Of particular interest in each of the two figures are estimates that capture the influence of women and men’s salience on the attention of women and men representatives. The US results in Figure 5 suggest that when holding constant the influence of the other variables in the series, women’s salience actually has a negative influence on the attention of men representatives. This indicates that men representatives ignore changes in women’s salience, likely focusing on different issues entirely or reducing their attention to issues that increase in salience for women constituents. In contrast, women’s salience is indeed a positive predictor of women representatives’ attention. Moreover, men’s salience is a positive predictor of the attention of both men and women representatives in the US. The influence of men’s salience appears to be a greater predictor than women’s salience for both women and men representatives in the US.

A similar pattern is observable in the UK results in Figure 6. In the UK, the estimates are larger in magnitude likely given that survey respondents can identify up to three issues that are believed to be the most important; however, within-country comparisons between men and women representatives reveal a similar pattern in the UK. Women’s salience is much less predictive of the attention of both men and women representatives compared to men’s salience. At the same time, women representatives are more responsive to changes in women and men’s salience than men representatives.

One advantage of the VAR models is that they allow for disentangling the direction of influence between the public and representatives. This is especially important given that the direction of influence is not always unidirectional. For example, it is possible that represen-

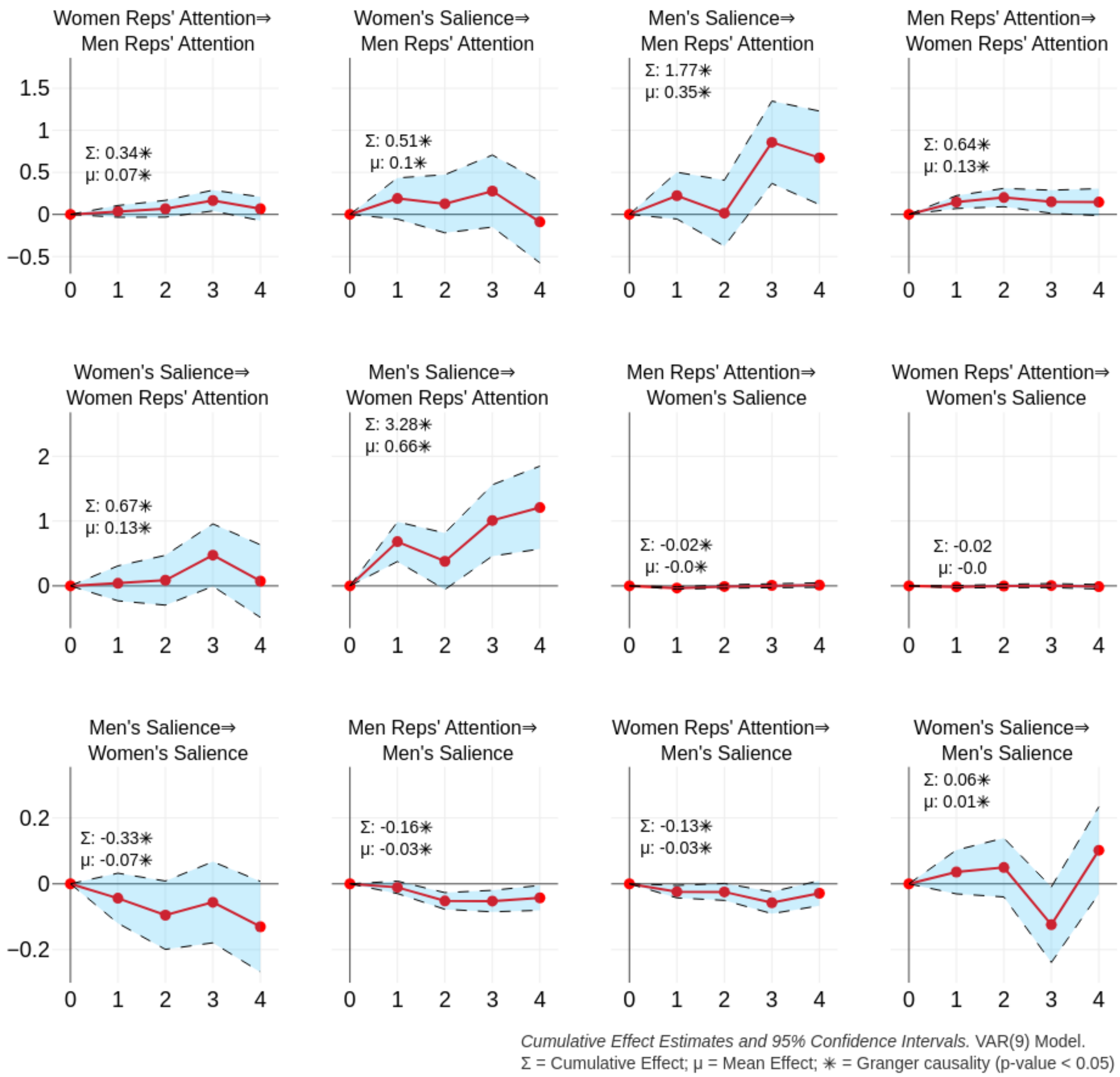
Figure 5: US Cumulative IRF Responses – Public Issue Salience and Representatives' Attention



Note: Cumulative IRF orthogonal effects from pooled VAR models that include women and men's issue priorities and MCs' attention. Dotted lines indicate 95% confidence intervals. The red lines represent the dynamic estimates, and the solid black lines indicate the cumulative effects over the course of four survey periods (Approximately five weeks). Full results presented in Appendix F.

tatives' attention influences public salience, rather than the other way around. This finding would be consistent with the idea that political elites are often able to shape public opinion (Ura 2014). In the US case, there is some support for this idea in the results. Namely, men representatives' attention appears to have a small but consistent influence on men's salience. However,

Figure 6: UK Cumulative IRF Responses – Public Issue Salience and Representatives' Attention



Note: Cumulative IRF orthogonal effects from pooled VAR models that include women and men's issue priorities and male and female representatives' issue attention. Dotted lines indicate 95% confidence intervals. The red lines represent the dynamic estimates, and the solid black lines indicate the cumulative effects over the course of four survey periods (Approximately five weeks). Full results presented in Appendix F.

this dynamic is not observable in the UK, and the results indicate that to the extent there is a relationship between representatives' attention and public salience, there is much greater evidence that the public shapes the attention of representatives than the other way around. This is highlighted by the fact that the influence of representatives' attention on public salience is close to zero and even negative in some cases.

Another advantage of the VAR models is that they allow for understanding how men and women representatives influence each other. In both countries, the influence appears to be small when controlling for the salience of both women and men separately.

Taken together, the results in Figure 6 and Figure 5 suggest that representatives are indeed responsive to public issue priorities, though the degree of responsiveness varies between the two countries and by gender makeup of public salience. In both countries, however, men's salience is a much better predictor of representatives' attention, indicating that representatives are more responsive to men in relation to women. Moreover, this finding holds regardless of the gender of the representative, as women representatives are more responsive to men than women. When it comes to responsiveness to women's salience, women representatives appear to be more responsive in both countries. This finding is consistent with the idea that women representatives are more likely to act in the interests of the women they represent (Lowande, Ritchie, and Lauterbach 2019; Funk and Philips 2019).

4.2 Fixed Effects Estimation

The results from the time series models indicate that women representatives are more responsive to the salience of a number of issues according to both men and women constituents. These results were consistent in both the US and the UK. To add robustness to the results, and to consider the individual level structure of the data, I additionally estimated a series of high-dimensional fixed-effects models with the individual level data. High-dimensional fixed effects models allow for multiple fixed effects parameters to be included in the same model by using maximum likelihood estimation (Bergé et al. 2018). These models therefore allow for including fixed effects parameters for each legislator, survey period and issue. The specification can be formalized as follows:

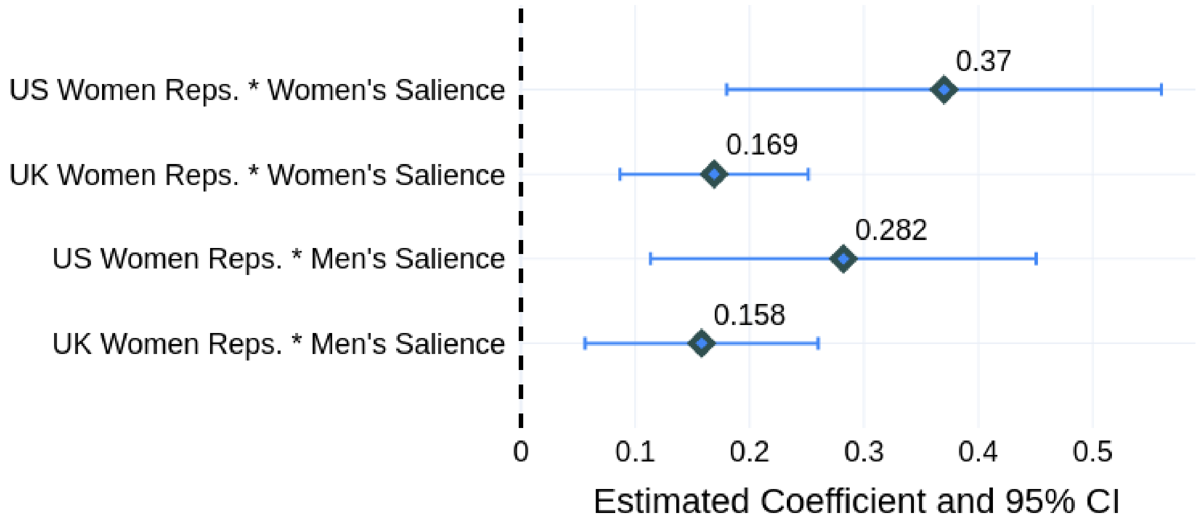
$$Y_{i,j,t} = MIP_{g,i,t} + Gender_i + (MIP_{g,i,t} \times Gender_i) + Z_{i,t} + \gamma_i + \delta_t + \lambda_j + \varepsilon_{g,i,t} \qquad (2)$$

Where $Y_{i,j,t}$ is the attention of representative i to issue j at time t. $MIP_{g,j,t}$ is the salience of issue j for constituents of gender g at time t, and is interacted with a binary variable ($Gender$) that captures the gender of the representative i. Z is the vote share received by legislator i at the previous election. γ_i, δ_t, λ_j are fixed effects parameters for each legislator, survey period and issue, respectively.

The parameter of interest is the interaction between the salience of issue i and the gender of the representative. This term captures the marginal effect of representatives' gender on responsiveness to the constituents identified in the MIP term (e.g. either women or men).

I present the results of the estimations in two ways. First, I present the full results in table form in Appendix G and Appendix H. Second, I present the results as a coefficient plot in Figure 7. Each estimated coefficient is from a separate model and indicates the marginal difference between women and men representatives responsiveness to either women or men constituents. The estimates are presented with 95% confidence intervals.

Figure 7: Marginal Effect Estimates for Responsiveness to Women and Men's Salience by Women Representatives



Note: Marginal effects estimates from the interaction between representatives' gender and issue salience for women and men in the US and UK. Standard errors are clustered by time and representative. Full results are presented in Appendix G and Appendix H. Estimates above correspond with Models 1 and 4 in the Appendix tables.

The results from the fixed effects models confirm the conclusions drawn from the time series models. In both the US and the UK, there is a stronger association between public salience and women representatives attention compared to men representatives. Moreover, these trends apply separately to both women and men's salience, as the issue salience according to either group is a better predictor of women representatives' attention than men representatives' attention. These results add robustness to the findings from the time series models and further highlight a gender gap in how men and women representatives allocate their attention to the issue priorities of the British and American public.

4.3 Robustness Tests

The results presented in the analysis paint a coherent picture, with women representatives more responsive in both countries to changes in the salience of both men and women constituents' issue salience. To ensure the results are robust to the assumptions made within the primary analyses, I considered several potential scenarios that may explain the observed results.

4.3.1 Alternative Model Specifications

To ensure the results are not driven by the specific model specification, I re-estimated the fixed effects models using Poisson regression with the same fixed effects parameters outlined in Equation 2. These count models use the number of tweets about a given issue that corresponds with the public opinion data as the dependent variable. The results suggest a statistically significant marginal difference between women and men representatives when responding to women's salience and men's salience in the UK. In the case of estimated the influence of men's salience on representatives' attention, the marginal difference between women and men does not meet the threshold for traditional levels of significance. Nonetheless, the results are consistent with the primary findings. I present the full results in Appendix J.

4.3.2 Position in Government

Although the primary analyses consider a large amount of data from many actors, there is only limited variation in which parties are in government. In the UK, the Conservative Party was in government for the entire period of the analysis, and in the US, the Democratic Party held a majority in the House of Representatives during most of the time of the analysis. To ensure that the results are not driven solely by the governing parties, I re-estimated the fixed effects models after sub-setting the data to only include Labour Party MPs in the UK and Republican Party MCs in the US. The results – presented in Appendix I – are consistent with the primary findings and similarly highlight that women representatives are more responsive to changes in women and men's issue salience when including only the minority/opposition party in each country.

Taken in full, the results from the primary analyses and the robustness checks confirm support for the hypothesis that women representatives are more responsive to changes in issue salience compared to men representatives. This finding is consistent across two countries and is robust to a number of alternative model specifications.

5 Discussion and Conclusion

A number of studies have shown that conditional on being elected, women in politics are more likely to act in the interests of their constituents (Anzia and Berry 2011; Thomsen and Sanders 2020). Yet, while these studies convincingly demonstrate that women representatives indeed are proactive in advancing the interests of constituents, the extent to which women representatives lead in responding to public opinion has remained unclear. Focusing on dynamic responsiveness, this study examined the degree to which representatives use social media to respond to the changing salience of public issue priorities. The findings reveal that while representatives in both countries are generally responsive to public opinion, there are important gender disparities in whose voices are heard. Across multiple empirical analyses, I find that dynamic salience of men constituents is more predictive of representatives' attention than the issue salience of women constituents. However, this gap is mitigated by the behavior of women representatives, who consistently shift their attention in line with the changing salience of women constituents. This over-performance by women representatives in responsiveness does not come at the expense of reduced responsiveness to men's priorities. Rather, men's issue salience is also a positive predictor of women representatives' attention – even more so than it is for men representatives' attention. In other words, women representatives are more responsive to women and men constituents than men representatives. These results were consistent across two countries and were robust to a number of alternative model specifications and robustness checks.

These results contribute to our understanding of elite-voter responsiveness and gender representation in several ways. First, the findings underscore the important representational benefits that women legislators provide – not only in terms of the substantive representation of women constituents, but for the electorate as a whole. In this regard, it is noteworthy that men receive greater responsiveness from women representatives than men representatives. This finding extends the over-performance argument beyond the findings of previous studies that point to over-performance of women on behalf of all constituents and instead suggests that men as a separate group also benefit from the over-performance of women elites.

Second, by moving beyond the proactive behaviors of representatives, the study creates a wider understanding of the ways in which women representatives lead in representing the interests of their constituents dynamically. Specifically, by focusing on representatives' dynamic communication outside of formal legislative settings, the study offers new insights into the ways in which public opinion shapes the communication strategies of representatives.

Finally, the study advances our understanding of how representatives may use alternative channels like social media to signal awareness of constituent priorities. Party discipline and political institutions can limit the ability of representatives to act in an individual capacity (Kam 2009; Clayton and Zetterberg 2021). However, social media mitigates some of these constraints and allows representatives to build individual policy reputations and to advance issue agendas (Russell 2021a, 2021b). This study extends that literature by showing that representatives also use social media as a means to respond to changes in the electorate's attitudes as well.

While the study provides a comprehensive analysis of gender disparities in issue responsiveness across two countries in the context of political communication on social media, several limitations and avenues for future research remain. First, there is a limit to the extent to which representatives' communication on social media can be interpreted as substantive representation. Although studies find that social media (and Twitter in particular) is important for voters who indeed prefer their representative emphasize their issue priorities online (Giger et al. 2021), talk is cheap and representatives are not obligated to follow through on promises made on social media. However, existing studies find high levels of correspondence between representatives' online behavior and their behavior within the legislature (Peeters, Van Aelst, and Praet 2021; Silva and Proksch 2022). Moreover, research also suggests that the public places a high value on the verbal representation of their issue priorities (Reher 2016), which indicates that voters may view this form of responsiveness as representation specifically. With that said, future studies may benefit from extending a similar type of dynamic analysis to include other forms of representative behavior, such as bill sponsorship or voting behavior.

A second consideration is in regards to the generalizability of the findings to other contexts. The study focuses on two countries with first-past-the-post electoral systems and single member districts. As the primary mechanisms behind the over-performance argument are thought to be related to the electoral system and the gendered nature of the political environment, contexts in which these factors are different may not produce the same patterns. Future studies may benefit from extending the analysis to other countries with different electoral systems and political environments.

A final limitation to the findings is that they are based on an analysis in which the "effect" of gender is not causally identified. As there are infinite characteristics endogenous to gender, this limitation serves as a word of caution when interpreting the results of the study in a causal way. Future studies may benefit from adopting a research design that allows for making more credible causal claims about the influence of gender on legislative behavior.

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Part I
Appendix

Table of Contents

A Public Opinion Data

Although all surveys used throughout the analysis were conducted by YouGov, the wording, date, and surveys differ in subtle ways. First, surveys conducted in the US require that respondents select only one issue that they identify as the most important issue facing the country. Surveys in the UK allow respondents to select up to three of the most important issues identified by the respondent. For this reason, I do not combine the two styles of surveys in the analysis and cross-country comparisons (i.e between Figures 1 and 2) should be made with caution.

The wording of the surveys was as follows:

1. UK: *"Which of the following do you think are the most important issues facing the country at this time? Please tick up to three."*

2. US: *"Which of these is the most important issue for you? Please note the following answer options were recorded:"*

There were several issues that were available at certain points in time for each of the countries that were combined with higher level issues. For example, "The War in Afghanistan" is a sub-issue of defense. An exhaustive list of the combinations that were made can be found below. All other issues that were options in the surveys reflect the issues used in the main text.

UK Survey Data

1. "Britain leaving the EU" → "International Affairs"
2. "Defense and security" → "Defense"
3. "Defense and terrorism" → "Defense"
4. "Afghanistan" → "Defense"

US Survey Data

1. "National Security and Foreign Policy" → "Defense"
2. "The war in Afganistan" → "Defense"
3. "Terrorism" → "Defense"

4. “Gun control” → “Crime”
5. “Crime and criminal justice reform” → “Crime”
6. “Medicare” → “Health”
7. “Health care” → “Health”
8. “Jobs and the economy” → “Economy”
9. “Inflation and prices” → “Economy”
10. “Inflation” → “Economy”
11. “Climate change and the environment” → “Environment”
12. “Taxes and government spending” → “Tax”

B Descriptive Statistics for Survey Data

Table A1: Descriptive Statistics for Public Opinion Survey Data

Country	Issue	Gender	Count	Mean	Std.	Min.	25%	50%	75%	Max.
UK	Crime	Men	182	0.19	0.06	0.09	0.14	0.19	0.23	0.38
UK	Crime	Women	182	0.19	0.07	0.07	0.14	0.20	0.24	0.39
UK	Defense	Men	182	0.11	0.04	0.05	0.08	0.10	0.13	0.25
UK	Defense	Women	182	0.09	0.04	0.03	0.06	0.08	0.12	0.29
UK	Economy	Men	182	0.42	0.12	0.27	0.31	0.40	0.54	0.65
UK	Economy	Women	182	0.36	0.15	0.18	0.22	0.32	0.53	0.61
UK	Education	Men	182	0.12	0.03	0.06	0.10	0.11	0.13	0.24
UK	Education	Women	182	0.16	0.04	0.10	0.13	0.15	0.17	0.32
UK	Environment	Men	182	0.23	0.07	0.08	0.18	0.24	0.28	0.38
UK	Environment	Women	182	0.24	0.08	0.10	0.18	0.25	0.30	0.42
UK	Health	Men	182	0.43	0.11	0.24	0.34	0.44	0.50	0.70
UK	Health	Women	182	0.53	0.11	0.32	0.44	0.55	0.61	0.81
UK	Immigration	Men	182	0.26	0.05	0.13	0.22	0.25	0.29	0.37
UK	Immigration	Women	182	0.24	0.06	0.09	0.20	0.23	0.29	0.41
UK	International Affairs (Brexit)	Men	182	0.51	0.17	0.24	0.32	0.53	0.66	0.77
UK	International Affairs (Brexit)	Women	182	0.46	0.17	0.19	0.26	0.46	0.62	0.73
UK	Tax	Men	182	0.06	0.02	0.02	0.04	0.05	0.06	0.13
UK	Tax	Women	182	0.03	0.02	0.01	0.03	0.03	0.04	0.11
US	Crime	Men	204	0.06	0.02	0.02	0.04	0.05	0.07	0.15
US	Crime	Women	204	0.06	0.02	0.02	0.05	0.06	0.08	0.14
US	Defense	Men	204	0.03	0.03	0.00	0.00	0.03	0.05	0.09
US	Defense	Women	204	0.04	0.04	0.00	0.00	0.04	0.06	0.12
US	Economy	Men	204	0.19	0.04	0.09	0.16	0.18	0.21	0.30
US	Economy	Women	204	0.14	0.04	0.08	0.11	0.13	0.16	0.25
US	Education	Men	204	0.05	0.01	0.02	0.04	0.05	0.05	0.09
US	Education	Women	204	0.06	0.01	0.03	0.05	0.06	0.07	0.10
US	Environment	Men	204	0.11	0.03	0.06	0.09	0.11	0.13	0.16
US	Environment	Women	204	0.11	0.03	0.05	0.09	0.11	0.13	0.21
US	Health	Men	204	0.18	0.03	0.11	0.16	0.18	0.20	0.29
US	Health	Women	204	0.24	0.04	0.13	0.22	0.24	0.26	0.34
US	Immigration	Men	204	0.12	0.04	0.03	0.09	0.12	0.15	0.22
US	Immigration	Women	204	0.09	0.03	0.03	0.06	0.09	0.12	0.16
US	Tax	Men	204	0.06	0.04	0.01	0.03	0.04	0.09	0.13
US	Tax	Women	204	0.04	0.02	0.01	0.02	0.04	0.06	0.11

C Descriptive Statistics for Twitter Data

The following table presents descriptive statistics for the Twitter data. The unit of analysis is legislator i for issue j at time t. Descriptive statistics only include tweets that address an issue.

Table A2: Descriptive Statistics for UK

Country	Gender	Party	Legislator				Tweets	Observations
			N	mean	std	min	max	N
UK	Female	Conservative	75	1.704769	5.591907	0.0	288.0	182
UK	Female	Democratic Unionist Party	1	1.920330	4.197400	0.0	57.0	182
UK	Female	Green Party	1	3.385714	6.941174	0.0	70.0	182
UK	Female	Independent	2	3.046703	13.828674	0.0	554.0	182
UK	Female	Labour	99	2.525125	7.425026	0.0	267.0	182
UK	Female	Liberal Democrat	8	2.505838	7.004927	0.0	135.0	182
UK	Female	Plaid Cymru	1	2.658242	7.826648	0.0	104.0	182
UK	Female	Scottish National Party	14	2.567425	8.824853	0.0	236.0	182
UK	Female	Sinn Féin	2	2.185440	6.509676	0.0	97.0	182
UK	Female	Social Democratic and Labour Party	1	3.225275	8.573186	0.0	95.0	182
UK	Male	Alliance Party of Northern Ireland	1	3.099451	5.796484	0.0	43.0	182
UK	Male	Conservative	238	1.627844	5.439029	0.0	310.0	182
UK	Male	Democratic Unionist Party	5	0.980659	2.955705	0.0	61.0	182
UK	Male	Independent	1	3.445055	13.352939	0.0	442.0	182
UK	Male	Labour	93	2.273189	6.725655	0.0	213.0	182
UK	Male	Liberal Democrat	4	2.916896	10.687796	0.0	291.0	182
UK	Male	Plaid Cymru	2	2.430220	7.525870	0.0	140.0	182
UK	Male	Scottish National Party	31	2.336813	8.790870	0.0	366.0	182
UK	Male	Sinn Féin	5	1.869231	6.001908	0.0	209.0	182
UK	Male	Social Democratic and Labour Party	1	2.551648	6.750324	0.0	78.0	182
UK	Male	Speaker	1	1.582967	5.151176	0.0	48.0	182

Table A3: Descriptive Statistics for US

Country	Gender	Party	Legislator				Tweets	Observations
			N	mean	std	min	max	N
US	Female	Democratic	88	2.159670	5.539469	0.0	229.0	204
US	Female	Republican	26	1.369400	4.995089	0.0	173.0	204
US	Male	Democratic	169	1.896325	5.339492	0.0	337.0	204
US	Male	Republican	225	1.516296	4.555784	0.0	261.0	204

D Validation of Language Model

To fine-tune the language model, I annotated 7,000 messages according to 9 issues: ('Economy', 'Tax', 'Environment', 'Immigration', 'Defense', 'International Affairs/Brexit', 'Education', 'Health', 'Crime', 'NA'). I then trained the model on these annotated messages, while holding out a test set for validation. Once the optimal hyperparameters for the model were selected using a grid search for weight decay, train/test size, learning rate and epochs, I validated the model's accuracy on the held out test set. Validation included using the fine-tuned model to predict the labels of the annotated messages that had not yet been used as training data. These predicted labels were compared to the labels that were originally annotated.

For validation metrics, I relied on the standard metrics of precision, recall and F1-score. Precision and recall are calculated as follows:

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

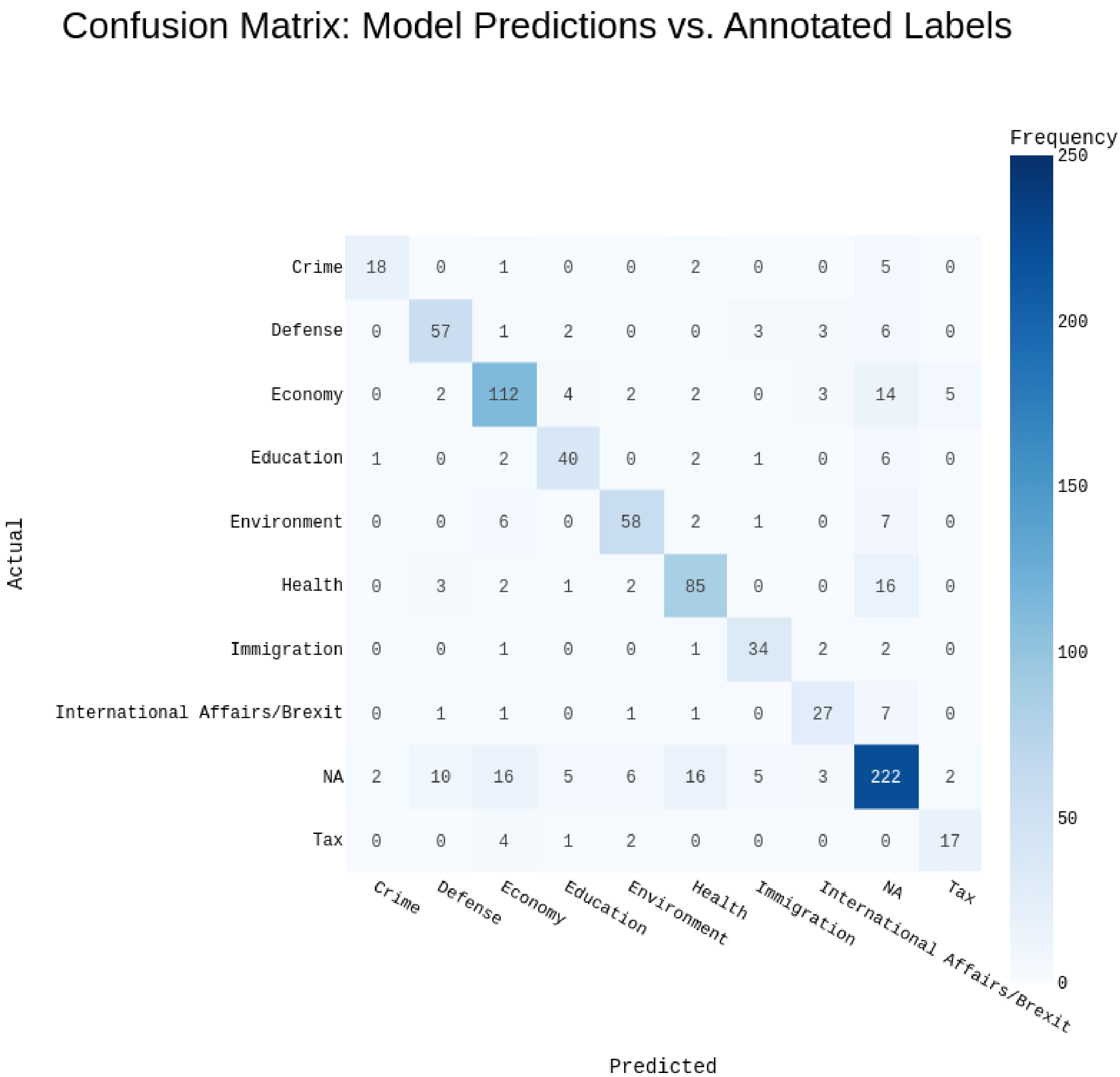
$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

F1-score, which is a standard metric for quantifying classification accuracy, is the harmonic mean of precision and recall. In addition to the F1 score, in multi-label classification settings, we can also calculate the precision and recall scores for each individual issue. Validation metrics, included multi-label F1 scores and a confusion matrix, are presented below in Table A4 and in Figure A1.

Table A4: Classification Report for Fine-Tuned Language Model

	Precision	Recall	F1-score	Support
Crime	0.86	0.64	0.73	28
Defense	0.76	0.79	0.78	72
Economy	0.77	0.78	0.77	144
Education	0.75	0.77	0.76	52
Environment	0.82	0.78	0.80	74
Health	0.77	0.78	0.77	109
Immigration	0.77	0.85	0.81	40
Brexit/International Affairs	0.71	0.71	0.71	38
NA	0.78	0.77	0.78	287
Tax	0.71	0.71	0.71	24
Accuracy			0.77	868
Macro Avg	0.77	0.76	0.76	868
Weighted Avg	0.77	0.77	0.77	868

Figure A1: Confusion Matrix for Model Predictions



E Granger Causality Tests

The following results are the output from the Granger Causality tests that were conducted to test the direction of the relationship between legislators' tweets and public opinion. Table A5 and Table A6 presents the results of the Granger Causality tests for the US and UK using the pooled data and time series for men and women's priorities and representatives' attention.

Table A5: Granger Causality Test Results – US

Coefficient	Test statistic	p-value	Critical value	df
Men Reps' Attention → Men Reps' Attention	16.2500	0	1.832	(10, 6228)
Men Reps' Attention → Women Reps' Attention	3.1590	0	1.832	(10, 6228)
Men Reps' Attention → Women's Salience	2.784	0.002	1.832	(10, 6228)
Men Reps' Attention → Men's Salience	2.131	0.019	1.832	(10, 6228)
Women Reps' Attention → Men Reps' Attention	6.776	0	1.832	(10, 6228)
Women Reps' Attention → Women Reps' Attention	7.810	0	1.832	(10, 6228)
Women Reps' Attention → Women's Salience	2.336	0.010	1.832	(10, 6228)
Women Reps' Attention → Men's Salience	4.125	0	1.832	(10, 6228)
Women's Salience → Men Reps' Attention	5.066	0	1.832	(10, 6228)
Women's Salience → Women Reps' Attention	4.245	0	1.832	(10, 6228)
Women's Salience → Women's Salience	10.870	0	1.832	(10, 6228)
Women's Salience → Men's Salience	7.622	0	1.832	(10, 6228)
Men's Salience → Men Reps' Attention	5.889	0	1.832	(10, 6228)
Men's Salience → Women Reps' Attention	4.328	0	1.832	(10, 6228)
Men's Salience → Women's Salience	4.089	0	1.832	(10, 6228)
Men's Salience → Men's Salience	10.340	0	1.832	(10, 6228)

Table A6: Granger Causality Test Results – UK

Coefficient	Test statistic	p-value	Critical value	df
Men Reps' Attention → Men Reps' Attention	4.360	0	1.881	(9, 6020)
Men Reps' Attention → Women Reps' Attention	3.328	0	1.881	(9, 6020)
Men Reps' Attention → Women's Salience	4.414	0	1.881	(9, 6020)
Men Reps' Attention → Men's Salience	4.152	0	1.881	(9, 6020)
Women Reps' Attention → Men Reps' Attention	2.996	0.001	1.881	(9, 6020)
Women Reps' Attention → Women Reps' Attention	2.459	0.009	1.881	(9, 6020)
Women Reps' Attention → Women's Salience	1.189	0.297	1.881	(9, 6020)
Women Reps' Attention → Men's Salience	3.304	0	1.881	(9, 6020)
Women's Salience → Men Reps' Attention	5.471	0	1.881	(9, 6020)
Women's Salience → Women Reps' Attention	6.408	0	1.881	(9, 6020)
Women's Salience → Women's Salience	4.731	0	1.881	(9, 6020)
Women's Salience → Men's Salience	10.760	0	1.881	(9, 6020)
Men's Salience → Men Reps' Attention	7.996	0	1.881	(9, 6020)
Men's Salience → Women Reps' Attention	5.381	0	1.881	(9, 6020)
Men's Salience → Women's Salience	4.137	0	1.881	(9, 6020)
Men's Salience → Men's Salience	10.530	0	1.881	(9, 6020)

F VAR Results for US and UK

Pooled estimates and summary statistics for VAR models with three variables (Reps' attention, men's salience and women's salience).

US results for pooled estimates for each of the three variables are presented in Table A7a, Table A7b, Table A8a and Table A8b.

UK results for pooled estimates for each of the three variables are presented in Table A9a, Table A9b, Table A10a and Table A10b.

Table A7: VAR Results for US

(a) US Male Representatives' Attention

Coefficient	Estimate	Std. error	T-stat	P-value
Const	0.011933	0.529853	0.023	0.982
L1. Men Rep's Attention	-0.001314	0.035002	-0.038	0.970
L1. Women Rep's Attention	0.044174	0.034708	1.273	0.203
L1.Women's Salience	-0.072309	0.053906	-1.341	0.180
L1.Men's Salience	0.221441	0.061149	3.621	0.000
L2. Men Rep's Attention	-0.025446	0.034871	-0.730	0.466
L2. Women Rep's Attention	0.051832	0.034565	1.500	0.134
L2.Women's Salience	0.068393	0.053962	1.267	0.205
L2.Men's Salience	0.001659	0.061458	0.027	0.978
L3. Men Rep's Attention	-0.017255	0.032825	-0.526	0.599
L3. Women Rep's Attention	-0.075929	0.033650	-2.256	0.024
L3.Women's Salience	-0.054109	0.052226	-1.036	0.300
L3.Men's Salience	-0.018555	0.060384	-0.307	0.759
L4. Men Rep's Attention	-0.165565	0.032861	-5.038	0.000
L4. Women Rep's Attention	0.031227	0.033682	0.927	0.354
L4.Women's Salience	-0.062904	0.052596	-1.196	0.232
L4.Men's Salience	-0.190631	0.060269	-3.163	0.002
L5. Men Rep's Attention	0.003964	0.033120	0.120	0.905
L5. Women Rep's Attention	0.037376	0.033660	1.110	0.267
L5.Women's Salience	-0.172318	0.052339	-3.292	0.001
L5.Men's Salience	0.243893	0.060281	4.046	0.000
L6. Men Rep's Attention	0.083403	0.033166	2.515	0.012
L6. Women Rep's Attention	-0.005351	0.033666	-0.159	0.874
L6.Women's Salience	0.027140	0.052720	0.515	0.607
L6.Men's Salience	-0.058992	0.060468	-0.976	0.329
L7. Men Rep's Attention	0.011974	0.033065	0.362	0.717
L7. Women Rep's Attention	0.057195	0.033589	1.703	0.089
L7.Women's Salience	0.133614	0.052621	2.539	0.011
L7.Men's Salience	-0.161914	0.060576	-2.673	0.008
L8. Men Rep's Attention	0.331137	0.033012	10.031	0.000
L8. Women Rep's Attention	0.232239	0.033529	6.926	0.000
L8.Women's Salience	0.226387	0.052234	4.334	0.000
L8.Men's Salience	0.141124	0.060810	2.321	0.020
L9. Men Rep's Attention	0.073662	0.035002	2.105	0.035
L9. Women Rep's Attention	0.040280	0.034507	1.167	0.243

(b) US Female Representatives' Attention

Coefficient	Estimate	Std. error	T-stat	P-value
const	-1.146898	0.531444	-2.158	0.031
L1. Men Rep's Attention	0.017345	0.035107	0.494	0.621
L1. Women Rep's Attention	0.040714	0.034812	1.170	0.242
L1.Women's Salience	-0.030797	0.054068	-0.570	0.569
L1.Men's Salience	0.244728	0.061332	3.990	0.000
L2. Men Rep's Attention	-0.012104	0.034976	-0.346	0.729
L2. Women Rep's Attention	0.023082	0.034669	0.666	0.506
L2.Women's Salience	0.167355	0.054124	3.092	0.002
L2.Men's Salience	-0.073043	0.061642	-1.185	0.236
L3. Men Rep's Attention	0.032797	0.032924	0.996	0.319
L3. Women Rep's Attention	-0.026441	0.033751	-0.783	0.433
L3.Women's Salience	-0.087153	0.052382	-1.664	0.096
L3.Men's Salience	0.101117	0.060565	1.670	0.095
L4. Men Rep's Attention	-0.029599	0.032960	-0.898	0.369
L4. Women Rep's Attention	-0.057210	0.033783	-1.693	0.090
L4.Women's Salience	-0.060695	0.052754	-1.151	0.250
L4.Men's Salience	-0.092587	0.060450	-1.532	0.126
L5. Men Rep's Attention	-0.048242	0.033220	-1.452	0.146
L5. Women Rep's Attention	-0.025780	0.033761	-0.764	0.445
L5.Women's Salience	-0.108104	0.052496	-2.059	0.039
L5.Men's Salience	0.009568	0.060462	0.158	0.874
L6. Men Rep's Attention	-0.007216	0.033265	-0.217	0.828
L6. Women Rep's Attention	0.004667	0.033767	0.138	0.890
L6.Women's Salience	-0.034788	0.052878	-0.658	0.511
L6.Men's Salience	-0.072303	0.060649	-1.192	0.233
L7. Men Rep's Attention	0.094228	0.033164	2.841	0.004
L7. Women Rep's Attention	0.104697	0.033690	3.108	0.002
L7.Women's Salience	0.162580	0.052779	3.080	0.002
L7.Men's Salience	-0.070983	0.060758	-1.168	0.243
L8. Men Rep's Attention	0.139324	0.033111	4.208	0.000
L8. Women Rep's Attention	0.245288	0.033630	7.294	0.000
L8.Women's Salience	0.157138	0.052391	2.999	0.003
L8.Men's Salience	-0.163335	0.060993	-2.678	0.007
L9. Men Rep's Attention	-0.014315	0.035107	-0.408	0.683
L9. Women Rep's Attention	0.023243	0.034610	0.672	0.502
L9.Women's Salience	-0.014384	0.053318	-0.270	0.787
L9.Men's Salience	-0.208087	0.061875	-3.363	0.001

(a) US Women's Salience

Coefficient	Estimate	Std. error	T-stat	P-value
const	-1.478567	0.333401	-4.435	0.000
L1. Men Rep's Attention	-0.011623	0.022024	-0.528	0.598
L1. Women Rep's Attention	-0.031565	0.021840	-1.445	0.148
L1.Women's Salience	-0.079769	0.033920	-2.352	0.019
L1.Men's Salience	-0.087106	0.038477	-2.264	0.024
L2. Men Rep's Attention	0.018984	0.021942	0.865	0.387
L2. Women Rep's Attention	-0.040322	0.021750	-1.854	0.064
L2.Women's Salience	-0.187852	0.033955	-5.532	0.000
L2.Men's Salience	0.020435	0.038671	0.528	0.597
L3. Men Rep's Attention	-0.004005	0.020655	-0.194	0.846
L3. Women Rep's Attention	-0.004664	0.021174	-0.220	0.826
L3.Women's Salience	-0.086820	0.032862	-2.642	0.008
L3.Men's Salience	0.104020	0.037995	2.738	0.006
L4. Men Rep's Attention	0.043564	0.020677	2.107	0.035
L4. Women Rep's Attention	-0.006584	0.021194	-0.311	0.756
L4.Women's Salience	0.090321	0.033095	2.729	0.006
L4.Men's Salience	0.090390	0.037923	2.383	0.017
L5. Men Rep's Attention	-0.029453	0.020840	-1.413	0.158
L5. Women Rep's Attention	-0.044292	0.021180	-2.091	0.037
L5.Women's Salience	0.043974	0.032934	1.335	0.182
L5.Men's Salience	-0.094321	0.037931	-2.487	0.013
L6. Men Rep's Attention	-0.051194	0.020869	-2.453	0.014
L6. Women Rep's Attention	0.001385	0.021184	0.065	0.948
L6.Women's Salience	-0.075102	0.033173	-2.264	0.024
L6.Men's Salience	0.113952	0.038048	2.995	0.003
L7. Men Rep's Attention	-0.027312	0.020805	-1.313	0.189
L7. Women Rep's Attention	-0.064187	0.021136	-3.037	0.002
L7.Women's Salience	-0.097148	0.033111	-2.934	0.003
L7.Men's Salience	0.031961	0.038117	0.839	0.402
L8. Men Rep's Attention	-0.000354	0.020772	-0.017	0.986
L8. Women Rep's Attention	-0.047469	0.021098	-2.250	0.024
L8.Women's Salience	0.129183	0.032868	3.930	0.000
L8.Men's Salience	0.054930	0.038264	1.436	0.151
L9. Men Rep's Attention	0.014929	0.022025	0.678	0.498
L9. Women Rep's Attention	0.011239	0.021713	0.518	0.605
L9.Women's Salience	0.082579	0.033449	2.469	0.014
L9.Men's Salience	0.089856	0.038818	2.315	0.021

(b) US Mens's Salience

Coefficient	Estimate	Std. error	T-stat	P-value
const	-1.307553	0.331435	-3.945	0.000
L1. Men Rep's Attention	0.021917	0.021895	1.001	0.317
L1. Women Rep's Attention	-0.024057	0.021711	-1.108	0.268
L1.Women's Salience	0.101889	0.033720	3.022	0.003
L1.Men's Salience	-0.225872	0.038250	-5.905	0.000
L2. Men Rep's Attention	0.024494	0.021813	1.123	0.261
L2. Women Rep's Attention	-0.019251	0.021621	-0.890	0.373
L2.Women's Salience	-0.067698	0.033755	-2.006	0.045
L2.Men's Salience	0.096016	0.038443	2.498	0.013
L3. Men Rep's Attention	0.021738	0.020533	1.059	0.290
L3. Women Rep's Attention	0.023295	0.021049	1.107	0.268
L3.Women's Salience	0.050428	0.032668	1.544	0.123
L3.Men's Salience	-0.012514	0.037771	-0.331	0.740
L4. Men Rep's Attention	0.043947	0.020555	2.138	0.033
L4. Women Rep's Attention	-0.001102	0.021069	-0.052	0.958
L4.Women's Salience	-0.004148	0.032900	-0.126	0.900
L4.Men's Salience	0.052905	0.037700	1.403	0.161
L5. Men Rep's Attention	0.021007	0.020717	1.014	0.311
L5. Women Rep's Attention	-0.015358	0.021055	-0.729	0.466
L5.Women's Salience	0.163192	0.032739	4.985	0.000
L5.Men's Salience	-0.155760	0.037707	-4.131	0.000
L6. Men Rep's Attention	-0.032510	0.020746	-1.567	0.117
L6. Women Rep's Attention	-0.005538	0.021059	-0.263	0.793
L6.Women's Salience	0.024283	0.032977	0.736	0.462
L6.Men's Salience	0.038936	0.037824	1.029	0.303
L7. Men Rep's Attention	-0.028480	0.020683	-1.377	0.169
L7. Women Rep's Attention	-0.047155	0.021011	-2.244	0.025
L7.Women's Salience	-0.128979	0.032916	-3.918	0.000
L7.Men's Salience	0.147024	0.037892	3.880	0.000
L8. Men Rep's Attention	-0.041262	0.020649	-1.998	0.046
L8. Women Rep's Attention	-0.112074	0.020973	-5.344	0.000
L8.Women's Salience	-0.067364	0.032674	-2.062	0.039
L8.Men's Salience	0.179647	0.038038	4.723	0.000
L9. Men Rep's Attention	-0.012559	0.021895	-0.574	0.566
L9. Women Rep's Attention	-0.016621	0.021585	-0.770	0.441
L9.Women's Salience	-0.026157	0.033252	-0.787	0.431
L9.Men's Salience	0.108340	0.038589	2.808	0.005

Table A9: VAR Results for UK

(a) UK Male Representatives' Attention

Coefficient	Estimate	Std. error	T-stat	P-value
const	-1.665926	0.993931	-1.676	0.094
L1. Men Rep's Attention	0.048350	0.035301	1.370	0.171
L1. Women Rep's Attention	0.036162	0.035646	1.014	0.310
L1.Women's Salience	0.189436	0.124836	1.517	0.129
L1.Men's Salience	0.223509	0.141655	1.578	0.115
L2. Men Rep's Attention	-0.002358	0.035302	-0.067	0.947
L2. Women Rep's Attention	0.035267	0.035697	0.988	0.323
L2.Women's Salience	-0.055258	0.123631	-0.447	0.655
L2.Men's Salience	-0.197076	0.141922	-1.389	0.165
L3. Men Rep's Attention	-0.030547	0.035024	-0.872	0.383
L3. Women Rep's Attention	0.085615	0.035543	2.409	0.016
L3.Women's Salience	0.147595	0.123184	1.198	0.231
L3.Men's Salience	0.793375	0.142210	5.579	0.000
L4. Men Rep's Attention	-0.060816	0.035015	-1.737	0.082
L4. Women Rep's Attention	-0.083294	0.035697	-2.333	0.020
L4.Women's Salience	-0.350632	0.123880	-2.830	0.005
L4.Men's Salience	-0.099957	0.143977	-0.694	0.488
L5. Men Rep's Attention	-0.091720	0.034955	-2.624	0.009
L5. Women Rep's Attention	0.039196	0.035796	1.095	0.274
L5.Women's Salience	-0.268693	0.124855	-2.152	0.031
L5.Men's Salience	0.208915	0.144092	1.450	0.147
L6. Men Rep's Attention	-0.038194	0.034783	-1.098	0.272
L6. Women Rep's Attention	-0.042051	0.035794	-1.175	0.240
L6.Women's Salience	-0.086816	0.124203	-0.699	0.485
L6.Men's Salience	-0.334680	0.142131	-2.355	0.019
L7. Men Rep's Attention	-0.059698	0.034281	-1.741	0.082
L7. Women Rep's Attention	0.089973	0.035812	2.512	0.012
L7.Women's Salience	0.657974	0.123379	5.333	0.000
L7.Men's Salience	-0.589387	0.142067	-4.149	0.000
L8. Men Rep's Attention	0.081338	0.033932	2.397	0.017
L8. Women Rep's Attention	0.061193	0.035754	1.712	0.087
L8.Women's Salience	-0.211429	0.121373	-1.742	0.082
L8.Men's Salience	0.125470	0.142260	0.882	0.378
L9. Men Rep's Attention	0.136650	0.033889	4.032	0.000
L9. Women Rep's Attention	0.053359	0.035871	1.488	0.137
L9.Women's Salience	-0.065217	0.121412	-0.537	0.591
L9.Men's Salience	0.288540	0.143292	2.014	0.044

(b) UK Female Representatives' Attention

Coefficient	Estimate	Std. error	T-stat	P-value
const	-1.198233	1.094677	-1.095	0.274
L1. Men Rep's Attention	0.146764	0.038880	3.775	0.000
L1. Women Rep's Attention	0.061908	0.039259	1.577	0.115
L1.Women's Salience	0.038758	0.137490	0.282	0.778
L1.Men's Salience	0.681461	0.156013	4.368	0.000
L2. Men Rep's Attention	0.046252	0.038880	1.190	0.234
L2. Women Rep's Attention	0.017520	0.039316	0.446	0.656
L2.Women's Salience	-0.001352	0.136162	-0.010	0.992
L2.Men's Salience	-0.257188	0.156308	-1.645	0.100
L3. Men Rep's Attention	-0.033003	0.038574	-0.856	0.392
L3. Women Rep's Attention	0.123718	0.039146	3.160	0.002
L3.Women's Salience	0.384230	0.135669	2.832	0.005
L3.Men's Salience	0.551685	0.156624	3.522	0.000
L4. Men Rep's Attention	-0.007896	0.038565	-0.205	0.838
L4. Women Rep's Attention	-0.052796	0.039316	-1.343	0.179
L4.Women's Salience	-0.288124	0.136436	-2.112	0.035
L4.Men's Salience	0.223803	0.158571	1.411	0.158
L5. Men Rep's Attention	-0.096378	0.038498	-2.503	0.012
L5. Women Rep's Attention	0.020970	0.039424	0.532	0.595
L5.Women's Salience	-0.373016	0.137510	-2.713	0.007
L5.Men's Salience	0.077839	0.158697	0.490	0.624
L6. Men Rep's Attention	-0.036795	0.038309	-0.960	0.337
L6. Women Rep's Attention	-0.045782	0.039422	-1.161	0.246
L6.Women's Salience	-0.255214	0.136792	-1.866	0.062
L6.Men's Salience	-0.367381	0.156538	-2.347	0.019
L7. Men Rep's Attention	0.038863	0.037756	1.029	0.303
L7. Women Rep's Attention	0.061082	0.039442	1.549	0.121
L7.Women's Salience	0.763527	0.135885	5.619	0.000
L7.Men's Salience	-0.300229	0.156467	-1.919	0.055
L8. Men Rep's Attention	0.051895	0.037371	1.389	0.165
L8. Women Rep's Attention	0.061628	0.039378	1.565	0.118
L8.Women's Salience	-0.015130	0.133675	-0.113	0.910
L8.Men's Salience	-0.204207	0.156679	-1.303	0.192
L9. Men Rep's Attention	0.062710	0.037324	1.680	0.093
L9. Women Rep's Attention	0.044656	0.039507	1.130	0.258
L9.Women's Salience	-0.187422	0.133718	-1.402	0.161
L9.Men's Salience	-0.131912	0.157816	-0.836	0.403

(a) UK Women's Salience

Coefficient	Estimate	Std. error	T-stat	P-value
const	-1.496981	0.272160	-5.500	0.000
L1. Men Rep's Attention	-0.032481	0.009666	-3.360	0.001
L1. Women Rep's Attention	-0.014076	0.009761	-1.442	0.149
L1.Women's Salience	-0.136430	0.034183	-3.991	0.000
L1.Men's Salience	-0.043784	0.038788	-1.129	0.259
L2. Men Rep's Attention	0.021132	0.009666	2.186	0.029
L2. Women Rep's Attention	0.012161	0.009775	1.244	0.213
L2.Women's Salience	-0.010216	0.033853	-0.302	0.763
L2.Men's Salience	-0.048276	0.038861	-1.242	0.214
L3. Men Rep's Attention	0.015756	0.009590	1.643	0.100
L3. Women Rep's Attention	0.005246	0.009732	0.539	0.590
L3.Women's Salience	-0.023093	0.033730	-0.685	0.494
L3.Men's Salience	0.003497	0.038940	0.090	0.928
L4. Men Rep's Attention	0.001646	0.009588	0.172	0.864
L4. Women Rep's Attention	-0.015224	0.009775	-1.558	0.119
L4.Women's Salience	-0.060792	0.033921	-1.792	0.073
L4.Men's Salience	-0.035403	0.039424	-0.898	0.369
L5. Men Rep's Attention	0.000644	0.009571	0.067	0.946
L5. Women Rep's Attention	0.004595	0.009802	0.469	0.639
L5.Women's Salience	0.031344	0.034188	0.917	0.359
L5.Men's Salience	0.066806	0.039455	1.693	0.090
L6. Men Rep's Attention	-0.014328	0.009524	-1.504	0.132
L6. Women Rep's Attention	-0.015079	0.009801	-1.538	0.124
L6.Women's Salience	-0.060231	0.034009	-1.771	0.077
L6.Men's Salience	-0.033811	0.038919	-0.869	0.385
L7. Men Rep's Attention	-0.002914	0.009387	-0.310	0.756
L7. Women Rep's Attention	-0.006971	0.009806	-0.711	0.477
L7.Women's Salience	-0.056516	0.033784	-1.673	0.094
L7.Men's Salience	0.098755	0.038901	2.539	0.011
L8. Men Rep's Attention	-0.028839	0.009291	-3.104	0.002
L8. Women Rep's Attention	-0.003104	0.009790	-0.317	0.751
L8.Women's Salience	0.072428	0.033235	2.179	0.029
L8.Men's Salience	-0.077028	0.038954	-1.977	0.048
L9. Men Rep's Attention	-0.028261	0.009279	-3.046	0.002
L9. Women Rep's Attention	-0.005179	0.009822	-0.527	0.598
L9.Women's Salience	0.129995	0.033245	3.910	0.000
L9.Men's Salience	-0.162965	0.039237	-4.153	0.000

(b) UK Mens's Salience

Coefficient	Estimate	Std. error	T-stat	P-value
const	-0.701104	0.270256	-2.594	0.009
L1. Men Rep's Attention	-0.010648	0.009599	-1.109	0.267
L1. Women Rep's Attention	-0.023674	0.009692	-2.442	0.015
L1.Women's Salience	0.035978	0.033944	1.060	0.289
L1.Men's Salience	-0.173055	0.038517	-4.493	0.000
L2. Men Rep's Attention	-0.038112	0.009599	-3.970	0.000
L2. Women Rep's Attention	-0.002602	0.009706	-0.268	0.789
L2.Women's Salience	0.027703	0.033616	0.824	0.410
L2.Men's Salience	0.082801	0.038589	2.146	0.032
L3. Men Rep's Attention	-0.003036	0.009523	-0.319	0.750
L3. Women Rep's Attention	-0.029033	0.009664	-3.004	0.003
L3.Women's Salience	-0.162909	0.033494	-4.864	0.000
L3.Men's Salience	-0.135350	0.038668	-3.500	0.000
L4. Men Rep's Attention	0.008068	0.009521	0.847	0.397
L4. Women Rep's Attention	0.024666	0.009706	2.541	0.011
L4.Women's Salience	0.188659	0.033684	5.601	0.000
L4.Men's Salience	-0.081773	0.039148	-2.089	0.037
L5. Men Rep's Attention	0.035648	0.009504	3.751	0.000
L5. Women Rep's Attention	-0.005858	0.009733	-0.602	0.547
L5.Women's Salience	0.064900	0.033949	1.912	0.056
L5.Men's Salience	-0.057348	0.039179	-1.464	0.143
L6. Men Rep's Attention	0.021288	0.009458	2.251	0.024
L6. Women Rep's Attention	0.025910	0.009733	2.662	0.008
L6.Women's Salience	0.079735	0.033771	2.361	0.018
L6.Men's Salience	0.146365	0.038646	3.787	0.000
L7. Men Rep's Attention	-0.000215	0.009321	-0.023	0.982
L7. Women Rep's Attention	-0.013565	0.009738	-1.393	0.164
L7.Women's Salience	-0.162841	0.033547	-4.854	0.000
L7.Men's Salience	0.043510	0.038629	1.126	0.260
L8. Men Rep's Attention	0.001957	0.009226	0.212	0.832
L8. Women Rep's Attention	-0.001646	0.009722	-0.169	0.866
L8.Women's Salience	0.007483	0.033002	0.227	0.821
L8.Men's Salience	0.152652	0.038681	3.946	0.000
L9. Men Rep's Attention	-0.001416	0.009215	-0.154	0.878
L9. Women Rep's Attention	-0.001928	0.009754	-0.198	0.843
L9.Women's Salience	-0.010614	0.033013	-0.322	0.748
L9.Men's Salience	0.184360	0.038962	4.732	0.000

G Fixed Effects Estimates – Women's Salience

Table A11: Responsiveness to Women's Issue Salience – Fixed Effects Results

Model:	US (1)	US (log attention) (2)	US (IVHS) (3)	UK (4)	UK (log attention) (5)	UK (IVHS) (6)
Variables						
Women's Salience	0.254***	0.117***	0.08***	0.641***	0.308***	0.206***
	(0.072)	(0.024)	(0.019)	(0.068)	(0.027)	(0.018)
Woman Rep. × Women's Salience	0.37***	0.082***	0.082***	0.169***	0.094***	0.065***
	(0.097)	(0.022)	(0.021)	(0.042)	(0.016)	(0.012)
Fixed-effects						
Total Tweets	✓		✓	✓		✓
Vote Share	✓	✓	✓	✓	✓	✓
Issue	✓	✓	✓	✓	✓	✓
Legislator	✓	✓	✓	✓	✓	✓
Party	✓	✓	✓	✓	✓	✓
Fit statistics						
R2	0.305	0.182	0.349	0.266	0.206	0.349
S.E. type	Time+Rep.	Time+Rep.	Time+Rep.	Time+Rep.	Time+Rep.	Time+Rep.
Observations	545,848	545,848	545,848	744,425	744,425	744,425

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: Standard errors clustered by legislator and survey date and are presented in parentheses. Models 1-3 include estimates for the US and Models 4-6 include estimates for the UK. The dependent variable is labeled above and includes different transformations. In Models 1 and 4, the number of issue tweets that correspond with the salience of the issue is used in natural form. In models 2 and 5, the logged value of attention (e.g. issue tweets/total tweets) is used. In Models 3 and 6, the DV is the inverse hyperbolic sine value of tweets (about the corresponding issue). All models include fixed effects for each legislator, survey period, party and issue and the legislator's vote share in the previous election as a covariate.

H Fixed Effects Estimates – Men's Issue Salience

Table A12: Responsiveness to Men's Issue Salience – Fixed Effects Results

Model:	US (1)	US (log attention) (2)	US (IVHS) (3)	UK (4)	UK (log attention) (5)	UK (IVHS) (6)
Variables						
Men's Salience	0.075	0.057*	0.032	0.817***	0.395***	0.26***
	(0.063)	(0.023)	(0.017)	(0.089)	(0.035)	(0.024)
Woman Rep. × Men's Salience	0.282**	0.053*	0.054**	0.158**	0.085***	0.061***
	(0.086)	(0.021)	(0.019)	(0.052)	(0.02)	(0.014)
Fixed-effects						
Total Tweets	✓		✓	✓		✓
Vote Share	✓	✓	✓	✓	✓	✓
Issue	✓	✓	✓	✓	✓	✓
Legislator	✓	✓	✓	✓	✓	✓
Party	✓	✓	✓	✓	✓	✓
Fit statistics						
R2	0.304	0.181	0.347	0.266	0.206	0.349
S.E. type	Time+Rep.	Time+Rep.	Time+Rep.	Time+Rep.	Time+Rep.	Time+Rep.
Observations	545,848	545,848	545,848	744,425	744,425	744,425

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: Standard errors clustered by legislator and survey date and are presented in parentheses. Models 1-3 include estimates for the US and Models 4-6 include estimates for the UK. The dependent variable is labeled above and includes different transformations. In Models 1 and 4, the number of issue tweets that correspond with the salience of the issue is used in natural form. In models 2 and 5, the logged value of attention (e.g. issue tweets/total tweets) is used. In Models 3 and 6, the DV is the inverse hyperbolic sine value of tweets (about the corresponding issue). All models include fixed effects for each legislator, survey period, and issue and the legislator's vote share in the previous election as a covariate.

I Robustness Check - UK Labour and US Republicans

The following results are robustness checks for the main findings in the paper. The first three models include estimates for the US (Republicans) and the last three models include estimates for the UK (Labour). The dependent variable is labeled above and includes different transformations. In Models 1 and 4, the number of issue tweets that correspond with the salience of the issue is used in natural form. In models 2 and 5, the logged value of attention (e.g. issue tweets/total tweets) is used. In Models 3 and 6, the DV is the inverse hyperbolic sine value of tweets (about the corresponding issue). All models include fixed effects for each legislator, survey period, and issue and the legislator's vote share in the previous election as a covariate.

Table A13: Responsiveness to **Women's** Issue Salience – UK Labour and US Republicans

Model:	US (1)	US (log attention) (2)	US (IVHS) (3)	UK (4)	UK (log attention) (5)	UK (IVHS) (6)
Variables						
Women's Salience	0.245***	0.108***	0.074***	0.881***	0.365***	0.272***
	(0.063)	(0.024)	(0.018)	(0.071)	(0.026)	(0.019)
Women Rep. × Women's Salience	0.265***	0.055***	0.047***	0.127***	0.058***	0.045***
	(0.04)	(0.011)	(0.008)	(0.015)	(0.007)	(0.005)
Fixed-effects						
Total Tweets	✓		✓	✓		✓
Vote Share	✓	✓	✓	✓	✓	✓
Issue	✓	✓	✓	✓	✓	✓
Legislator	✓	✓	✓	✓	✓	✓
Party	✓	✓	✓	✓	✓	✓
Fit statistics						
R2	0.275	0.159	0.307	0.302	0.251	0.39
S.E. type	by: Time	by: Time	by: Time	by: Time	by: Time	by: Time
Observations	257178	257178	257178	233996	233996	233996

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: Standard errors presented in parentheses. Models 1-3 include estimates for the US (Republicans) and Models 4-6 include estimates for the UK (Labour). The dependent variable is labeled above and includes different transformations. In Models 1 and 4, the number of issue tweets that correspond with the salience of the issue is used in natural form. In models 2 and 5, the logged value of attention (e.g. issue tweets/total tweets) is used. In Models 3 and 6, the DV is the inverse hyperbolic sine value of tweets (about the corresponding issue). All models include fixed effects for each legislator, survey period, and issue and the legislator's vote share in the previous election as a covariate.

Table A14: Responsiveness to **Men's** Issue Salience – UK Labour and US Republicans

Model:	US (1)	US (log attention) (2)	US (IVHS) (3)	UK (4)	UK (log attention) (5)	UK (IVHS) (6)
Variables						
Men's Salience	0.075	0.057**	0.032	0.817***	0.395***	0.26***
	(0.057)	(0.022)	(0.016)	(0.079)	(0.032)	(0.021)
Women Rep. × Men's Salience	0.282***	0.053***	0.054***	0.158***	0.085***	0.061***
	(0.026)	(0.006)	(0.005)	(0.013)	(0.005)	(0.004)
Fixed-effects						
Total Tweets	✓		✓	✓		✓
Vote Share	✓	✓	✓	✓	✓	✓
Issue	✓	✓	✓	✓	✓	✓
Legislator	✓	✓	✓	✓	✓	✓
Party	✓	✓	✓	✓	✓	✓
Fit statistics						
R2	0.304	0.181	0.347	0.266	0.206	0.349
S.E. type	by: Time	by: Time	by: Time	by: Time	by: Time	by: Time
Observations	257178	257178	257178	233996	233996	233996

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: Standard errors presented in parentheses. Models 1-3 include estimates for the US (Republicans) and Models 4-6 include estimates for the UK (Labour). The dependent variable is labeled above and includes different transformations. In Models 1 and 4, the number of issue tweets that correspond with the salience of the issue is used in natural form. In models 2 and 5, the logged value of attention (e.g. issue tweets/total tweets) is used. In Models 3 and 6, the DV is the inverse hyperbolic sine value of tweets (about the corresponding issue). All models include fixed effects for each legislator, survey period, and issue and the legislator's vote share in the previous election as a covariate.

J Poisson Fixed Effects Estimates

The following tables present the results of the Poisson fixed effects models for the US and UK. The dependent variable is the number of tweets about an issue.

Dependent Variable:	Tweets			
Model:	US	UK	US	UK
Variables				
Men's Salience	0.322***		0.590***	
	(0.060)		(0.063)	
Men's Salience × Women Rep.	0.068*		0.015	
	(0.038)		(0.039)	
Women's Salience		0.382***		0.368***
		(0.057)		(0.053)
Women's Salience × Women Rep.		0.111**		0.079**
		(0.044)		(0.038)
Vote share	-0.897	-0.889	0.139	0.167
	(0.619)	(0.618)	(0.744)	(0.743)
Fixed-effects				
Rep.	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes
Issue	Yes	Yes	Yes	Yes
Party	Yes	Yes	Yes	Yes
Fit statistics				
Observations	545,848	545,848	744,425	744,425
Squared Correlation	0.29751	0.29927	0.24097	0.23696
Pseudo R^2	0.28421	0.28527	0.28147	0.28002
BIC	1,904,711.6	1,901,906.2	2,061,330.9	2,065,467.1

Clustered (Time & Rep.) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*